Elaborazione del Linguaggio Naturale: Interpretazione, Ragionamento automatico e Apprendimento delle macchine

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dblp: http://dblp.uni-trier.de/pers/hd/b/Basili:Roberto.html

Google scholar: https://scholar.google.com/citations?user=U1A22fYAAAAJ&hl=it&oi=sra

Università di Bologna, 16 Maggio 2016

Overview

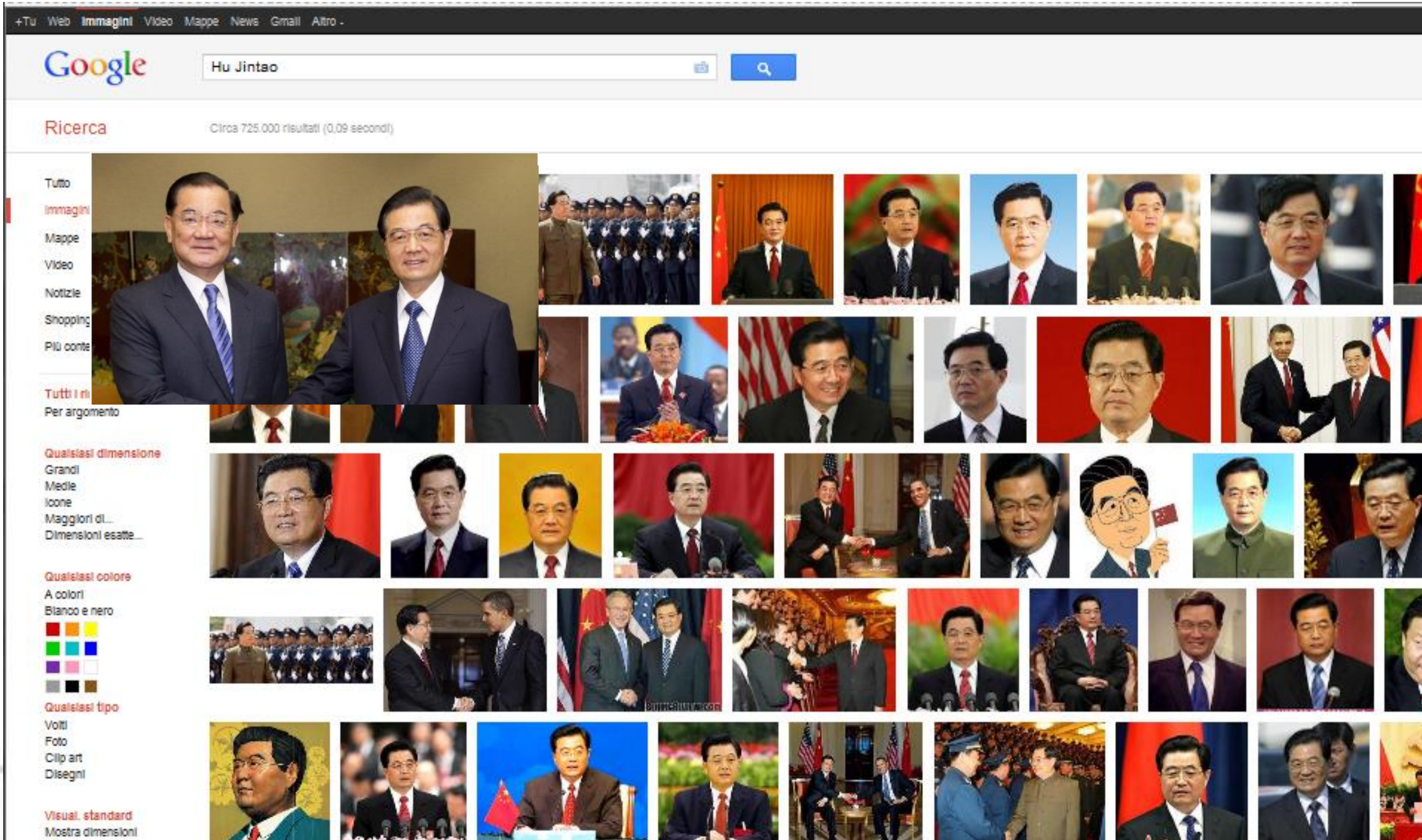
- Intelligenza Artificiale e Lingue parlate e scritte
  - Informazioni e Rappresentazioni coinvolte
  - Sfide (ri)correnti, battaglie (già) vinte e rischi inerenti …
- Elaborazione Automatica delle Lingue: Modelli, Metodi e *Risultati*
- *break*
- Ruolo delle Tecnologie dell'Apprendimento ed Applicazioni:
  - Sviluppo Automatico di Dizionari, Lessici Semantici ed Ontologie
  - Riconoscimento di fenomeni semantici
  - Trattamento Semantico della Documentazione Investigativa
  - Sistemi Web-based di Opinion Mining, Market Watch & Brand Reputation Management

Semantics, Open Data and Natural Language

Web contents, characterized by rich multimedia information, are mostly opaque from a semantic standpoint

Information, Web and Natural Languages

Who is Hu Jintao?



+Tu Web Immagini Video Mappe News Gmail Altro -
Google
Hu Jintao
Ricerca
Circa 725.000 risultati (0,09 secondi)
Tutto
Mappe
Video
Notizie
Per argomento
Qualsiasi dimensione
Grandi
Medie
Icone
Maggiori di...
Dimensioni esatte...
Qualsiasi colore
A colori
Bianco e nero
Qualsiasi tipo
Volti
Foto
Clip art
Disegni
Visual. standard
Mostra dimensioni

Content Semantics and Natural Language

- Human languages are the main carrier of the information involved in processes such as *retrieval*, *publication* and *exchange* of knowledge as it is associated to the open Web contents
- Words and NL syntactic structures express concepts, activities, events, abstractions and conceptual relations we usually share through data
- "*Language is parasitic to knowledge representation languages but the viceversa is not true*" (Wilks, 2001)
- From **Learning to Read** to **Knowledge Distillation** as a (integrated pool of) Semantic interpretation Task(s)

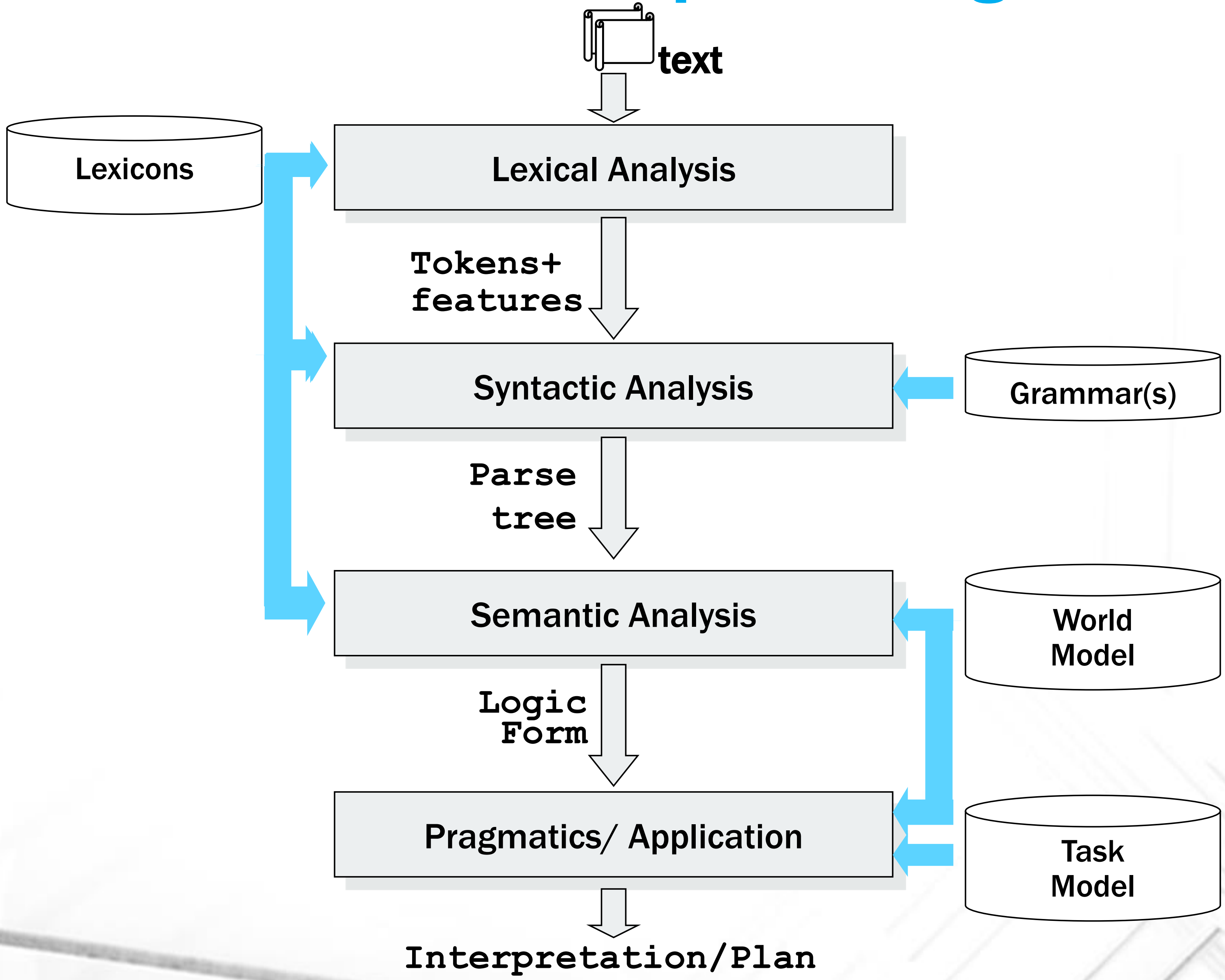
Semantics, Natural Language & Learning: tasks

- From Learning to Read to Knowledge Distillation as a (integrated pool of)

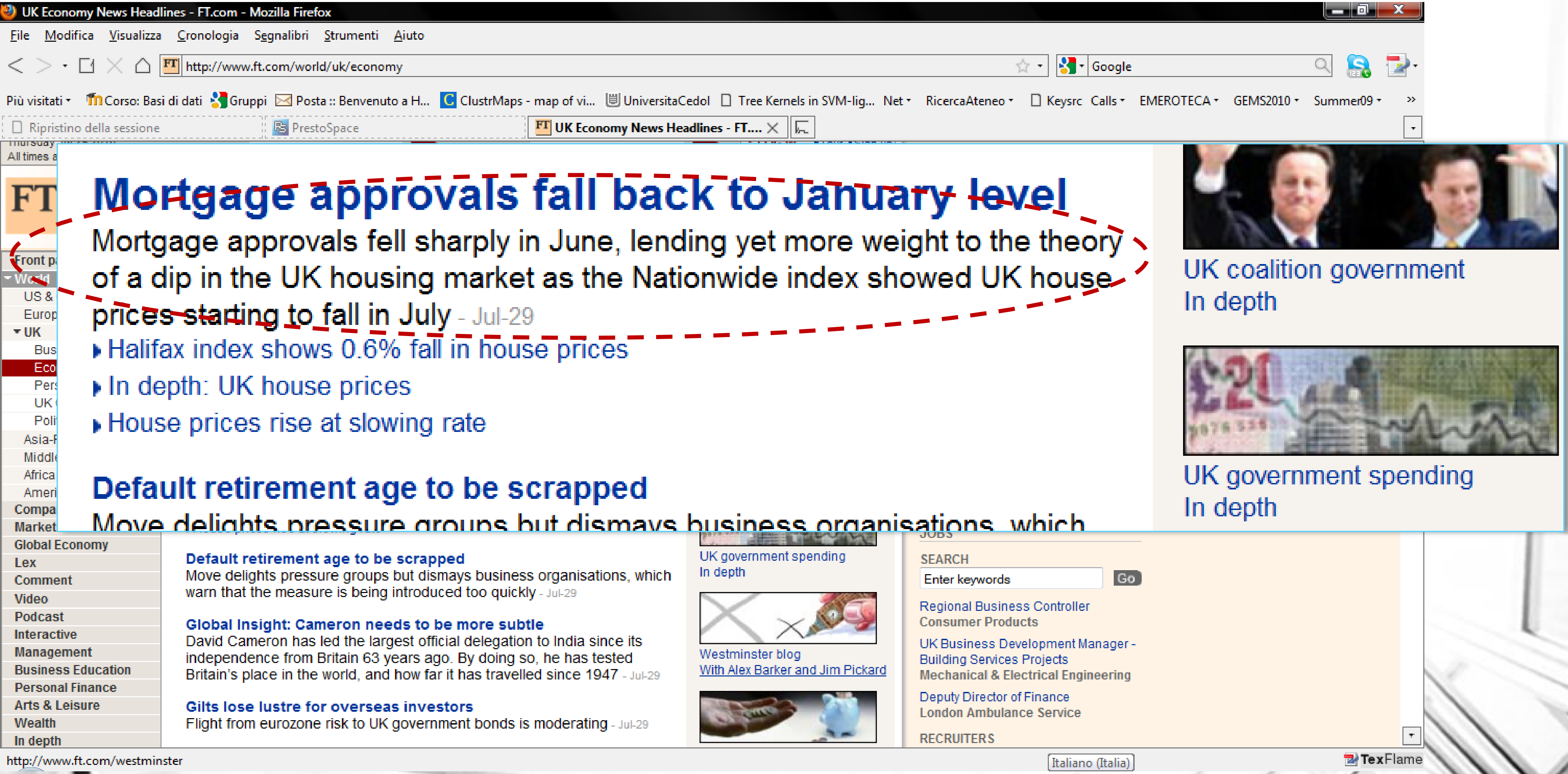
  Semantic interpretation Task(s)

  - **Information Extraction**
    - Entity Recognition and Classification
    - Relation Extraction
    - Semantic Role Labeling (Shallow Semantic Parsing)
  - **Estimation of Text Similarity**
    - Structured Text Similarity/Textual Entailment Recognition
    - Sense disambiguation
  - **Semantic Search, Question Classification and Answer Ranking**
  - **Knowledge Acquisition**, e.g. ontology learning
  - **Social Network Analysis, Opinion Mining**

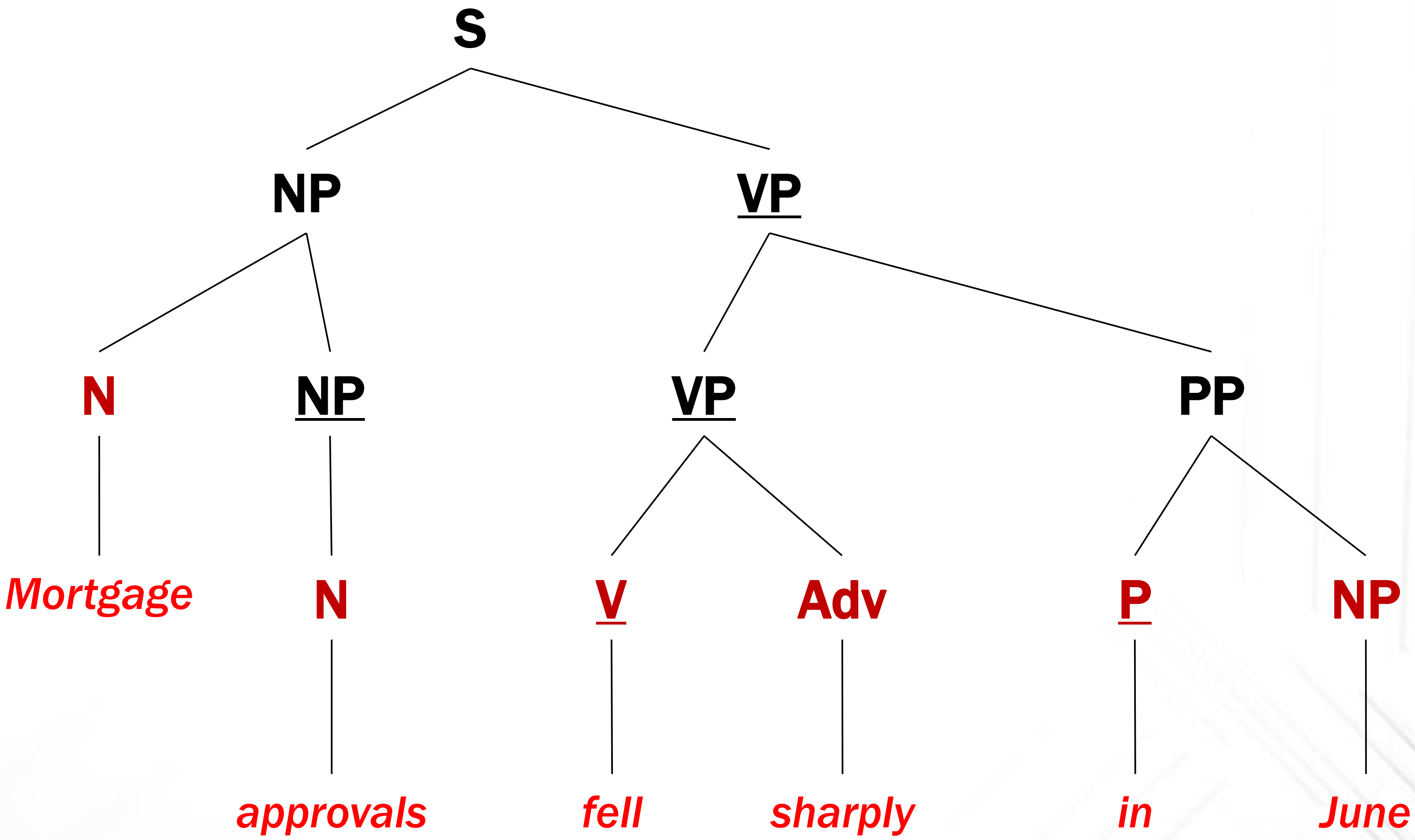
NLP: the standard processing chain

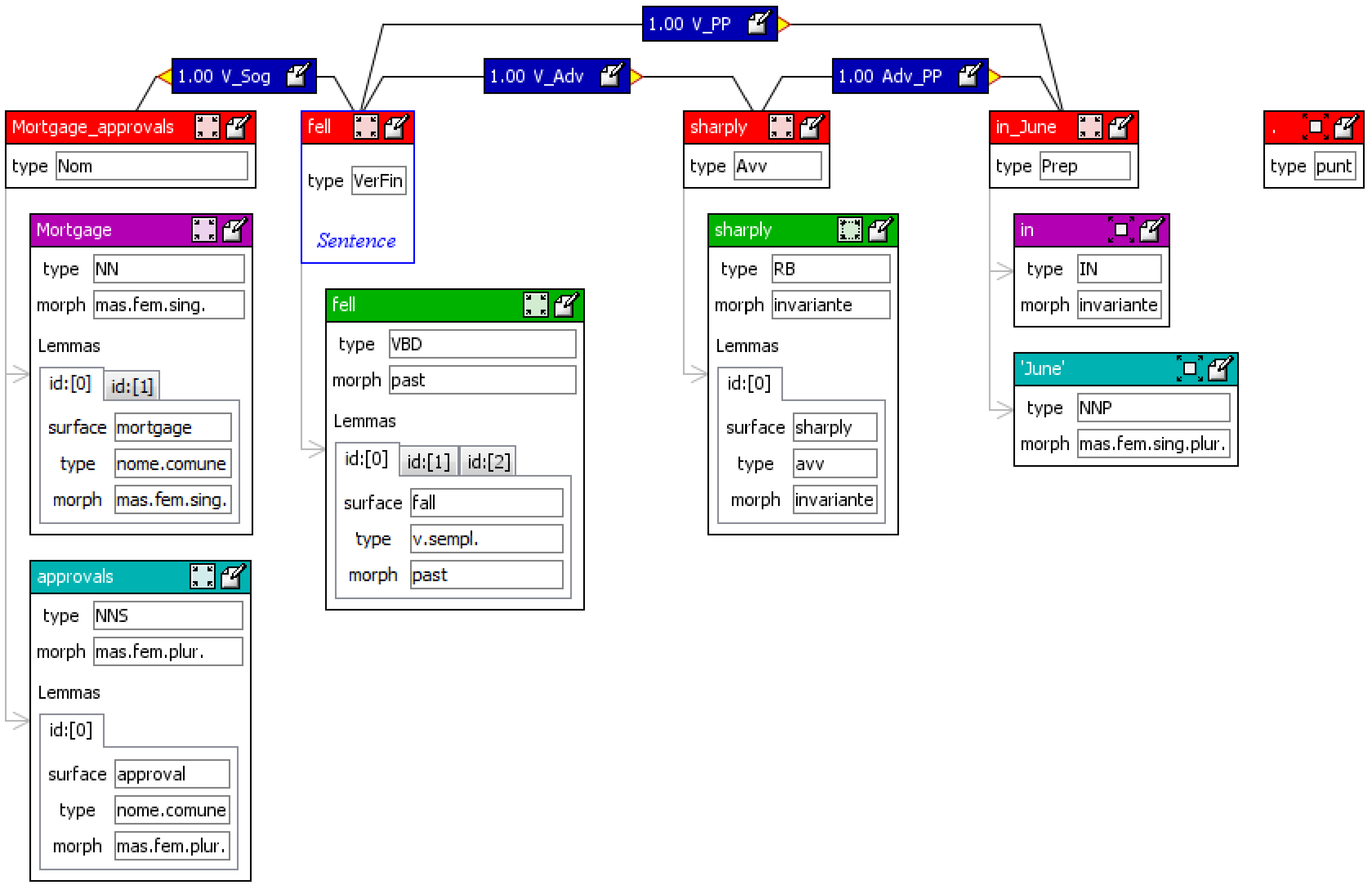


Grammatical Analysis

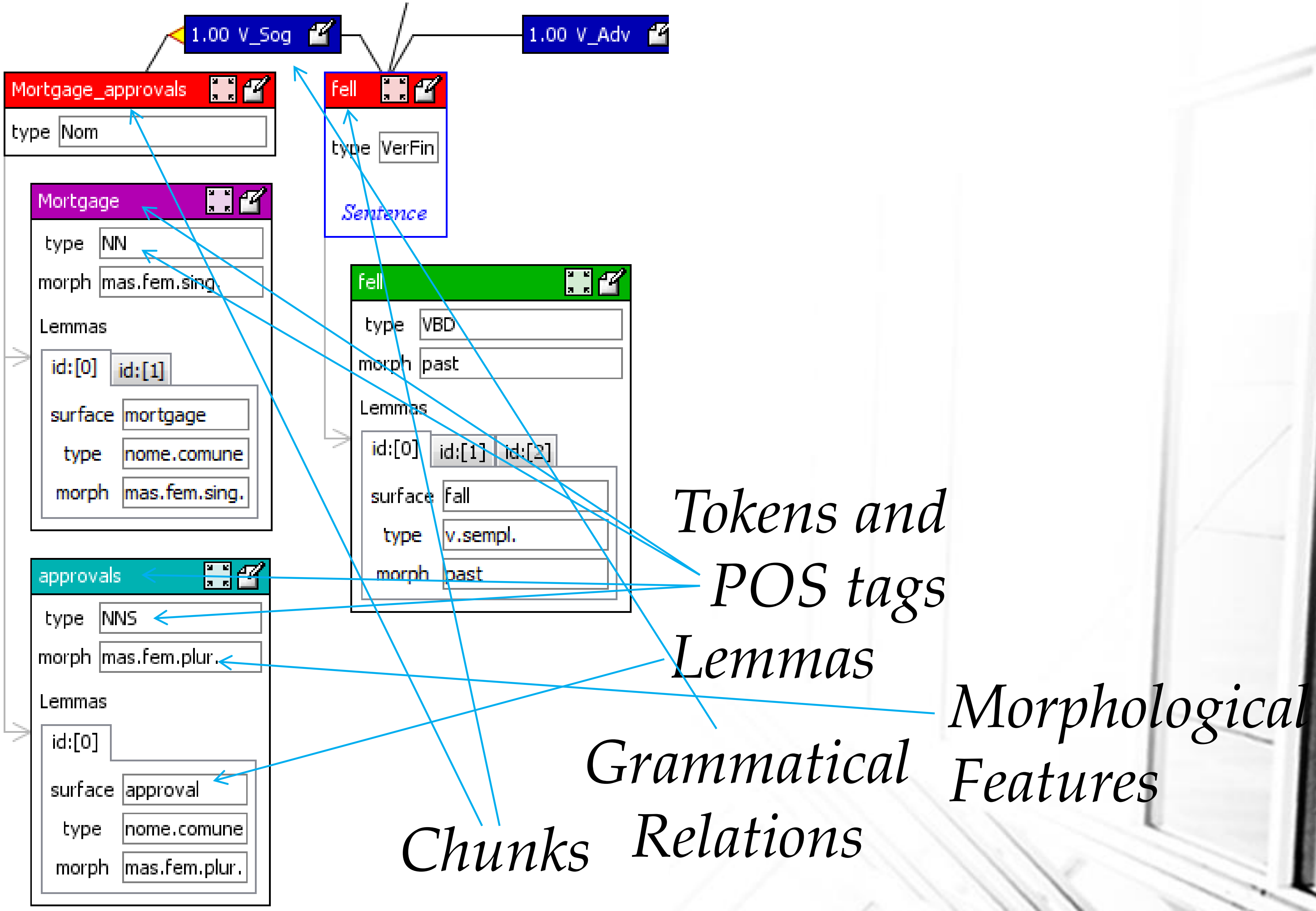


Constituency-based Parsing





FT (July, 29): ***Mortgage approvals fell sharply in June.***



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Challenges for Parsing

- Huge complexity as for the ambiguity in the morphosyntactic descriptions of words
  - E.g. La vecchia porta la sbarra
- Interdependency with semantic information
  - Most ambiguity cannot be solved only at the grammatical level
  - Lexical Semantic information is crucial as grammatical structures are constrained by word senses
    - Operating in a market vs. Operating a patient

Semantics

- What is the meaning of the sentence

  John saw Kim?

- Desirable Properties:
  - **It should be derivable as a function of the indivdual constituents,** i.e. the meanings of costituents such as *Kim*, *John* and *see*
  - **Independent from syntactic phenomena**, e.g. *Kim was seen by John* is a paraphrasis
  - It must be directy used to trigger some **inferences:**
    - *Who was seen by John? Kim!*
    - *John saw Kim. He started running to her.*

A Truth conditional semantics

S
saw(s,k)

NP
s

Sam
s

VP
{ x : saw(x,k)}

V
{ <x,y> : saw(x,y)}

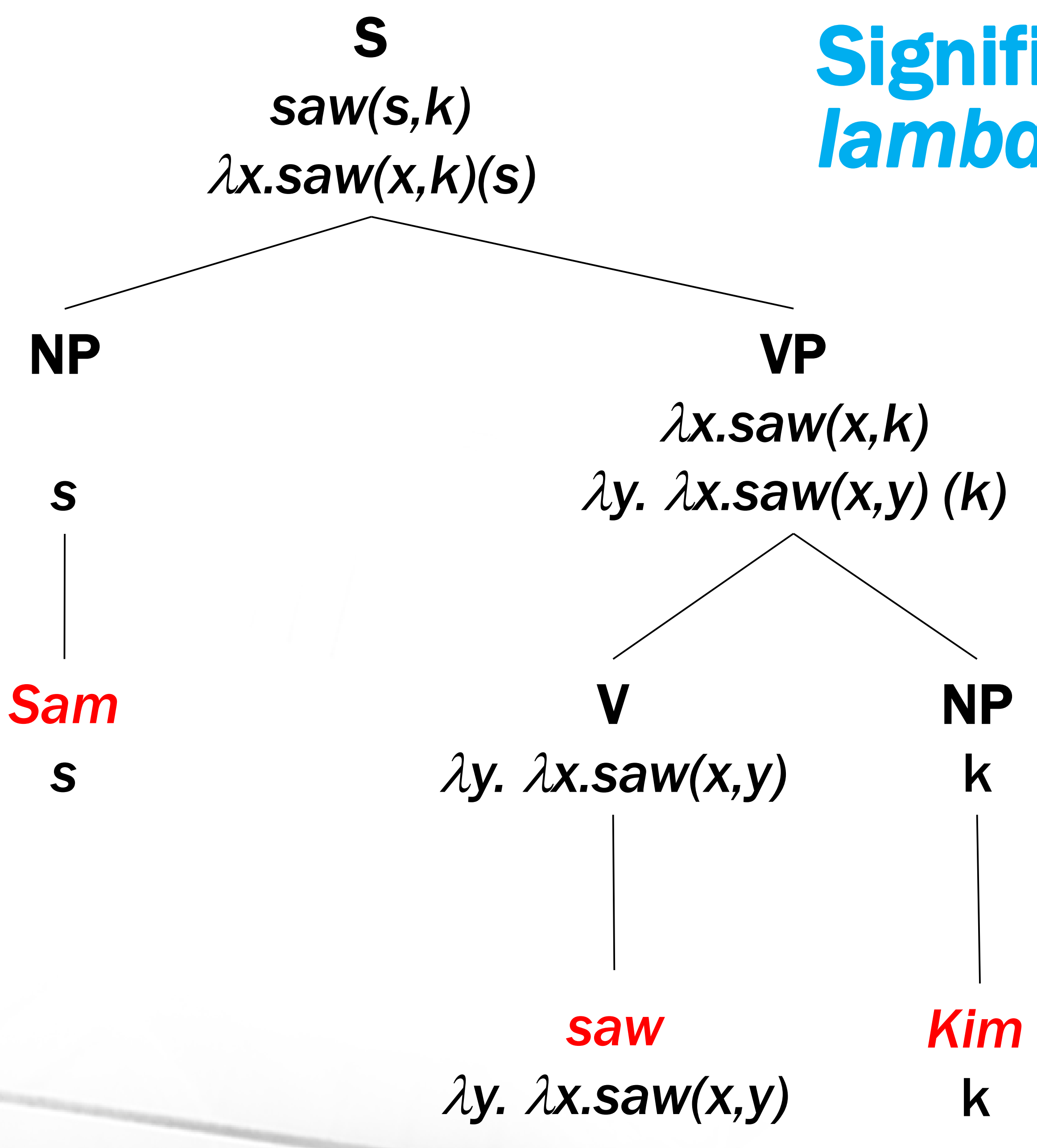
saw
{ <x,y> : saw(x,y)}

NP
k

Kim
k

John saw Kim

Significato come calcolo di *lambda espressioni*



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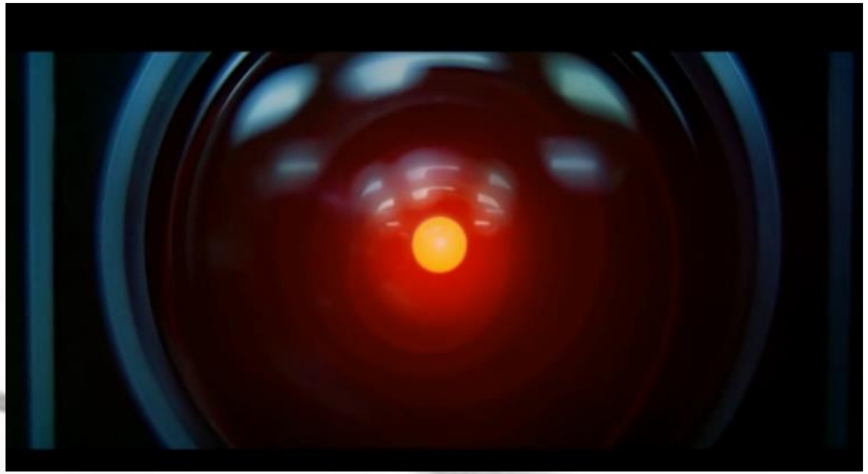
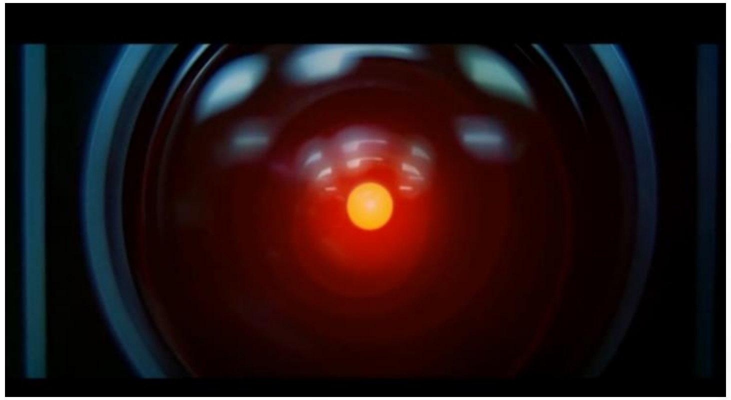
Which Knowledge?

- HAL 9000, da "*2001: A Space Odyssey*"

- Dave: *Open the pod bay doors, Hal*.
- HAL: *I'm sorry Dave, I'm afraid I can't do that*.

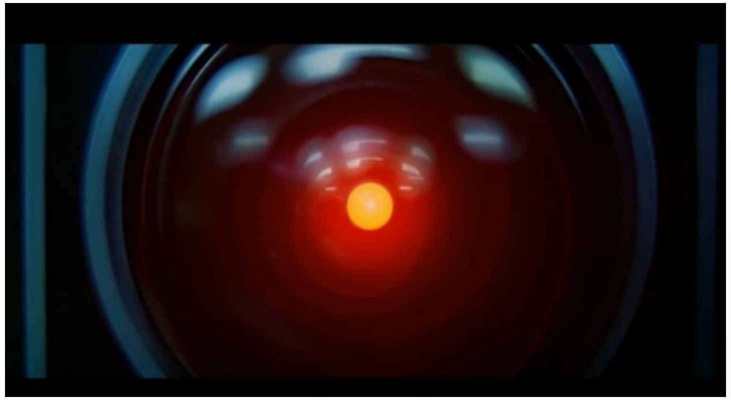


What’s HAL knowledge?



- **Recognition & Synthesis of spoken language**
  - Dictionaries (spelling)
  - Phonetics (how to produce/recognize sound)
- **Understanding**
  - **Lexical Knowledge**
    - What do the words mean?
    - How they combine (`*pod bay door*’)
  - **Knowledge about the syntagmatic structure of sentences**
    - *I’m I do, Sorry that afraid Dave I’m can’t*

What’s HAL knowledge?



- **Dialogue & pragmatics**
  - “*open the door*” is a request (and not a declaration or a search query)
  - Replying is a type of action that imply kindness (even if a planning to kill is in progress …)
  - It is useful to behave cooperatively (*I’m afraid, I can’t…*)
  - What about `*that*’ in `*I can’t do that*’?

Language Processing as a (*semantic*) *interpretation process*

- Processing a text corresponds to understand a number of aspects related to its *meaning*
  - Thematic Domain (e.g. science/housekeeping/economics)
  - Operational Objectives (e.g. e-mail *spam*)
  - Involved Entitites, such as people or locations
  - Potential events described (e.g. facts told by news)
  - Obbiettivi comunicativi (e.g. dialogue, orders/declarations/planning)
- Outcome: an explicit *representation of the text meaning* ...
- able to trigger different inferences
  (e.g. IR *relevance, planning*, knowledge updates, ...)

Some Reflections

- Understading *linguistic information* requires specific knowledge about:
  - The natural language itself (e.g. *grammar*)
  - The world (e.g. *bay door*, *Dave* or *opening*)
  - How language make **reference** to the world
- NLP applications deals with texts by exploiting the specific context:
  - Application purposes, e.g. document search
  - The domain and the operational context of an application
  - The distinction between language producer (speaker/writer) and consumer (hearer/reader)

Major Challenges

- *Linguistic Accuracy* in approximating the human-level of performance
- *Robustness* (errors/noise/incompleteness)
- *Scale*
  - Coverage of the phenomena (Lexicons/Grammars)
- *Expressivity*
  - Dictionaries, Lexicons and *Thesauri*
  - World Models and types of inference
- *Flexibility*
  - Adequate performance across linguistic variability (e.g. producer vs. consumer)
- *Naturalness*

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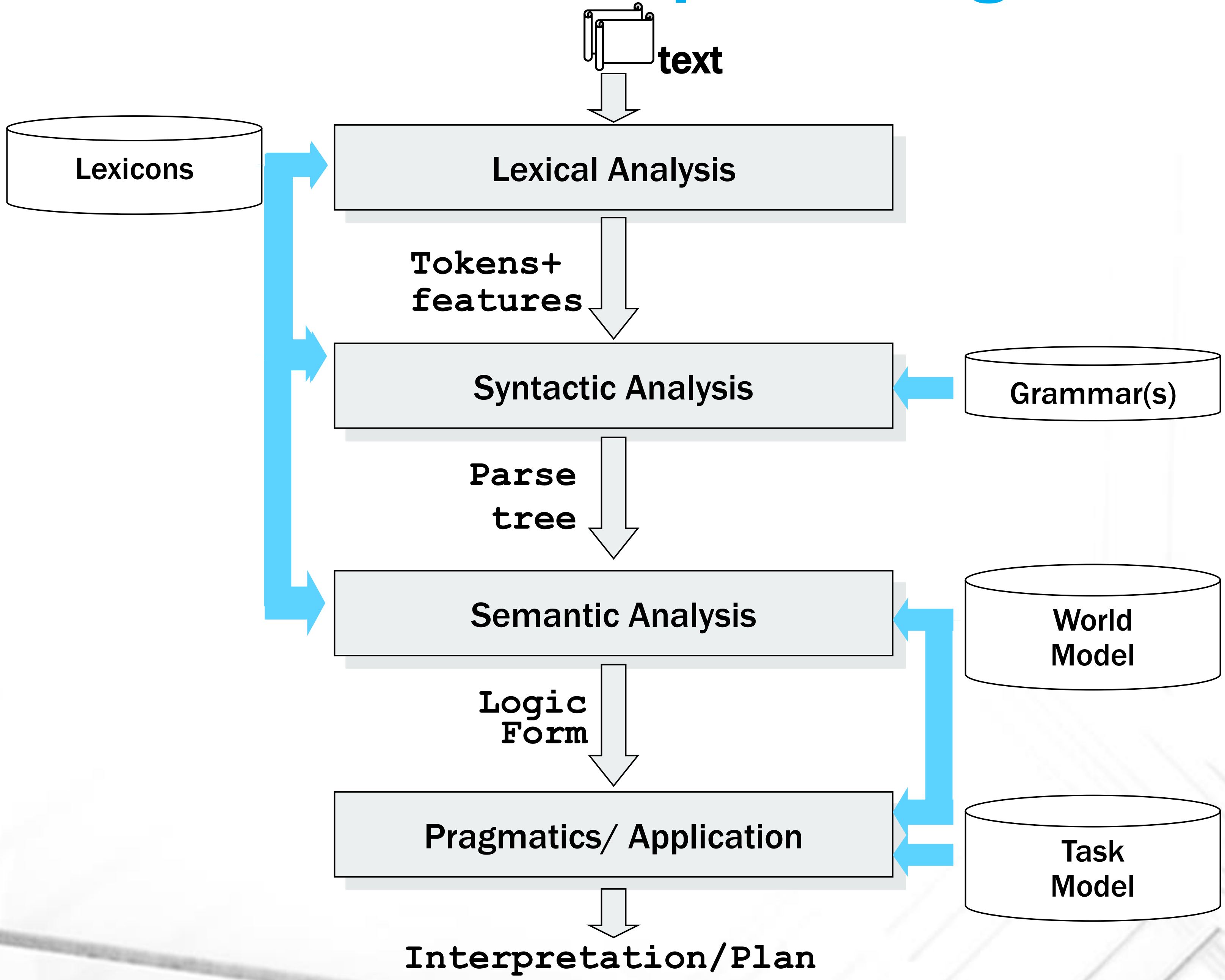

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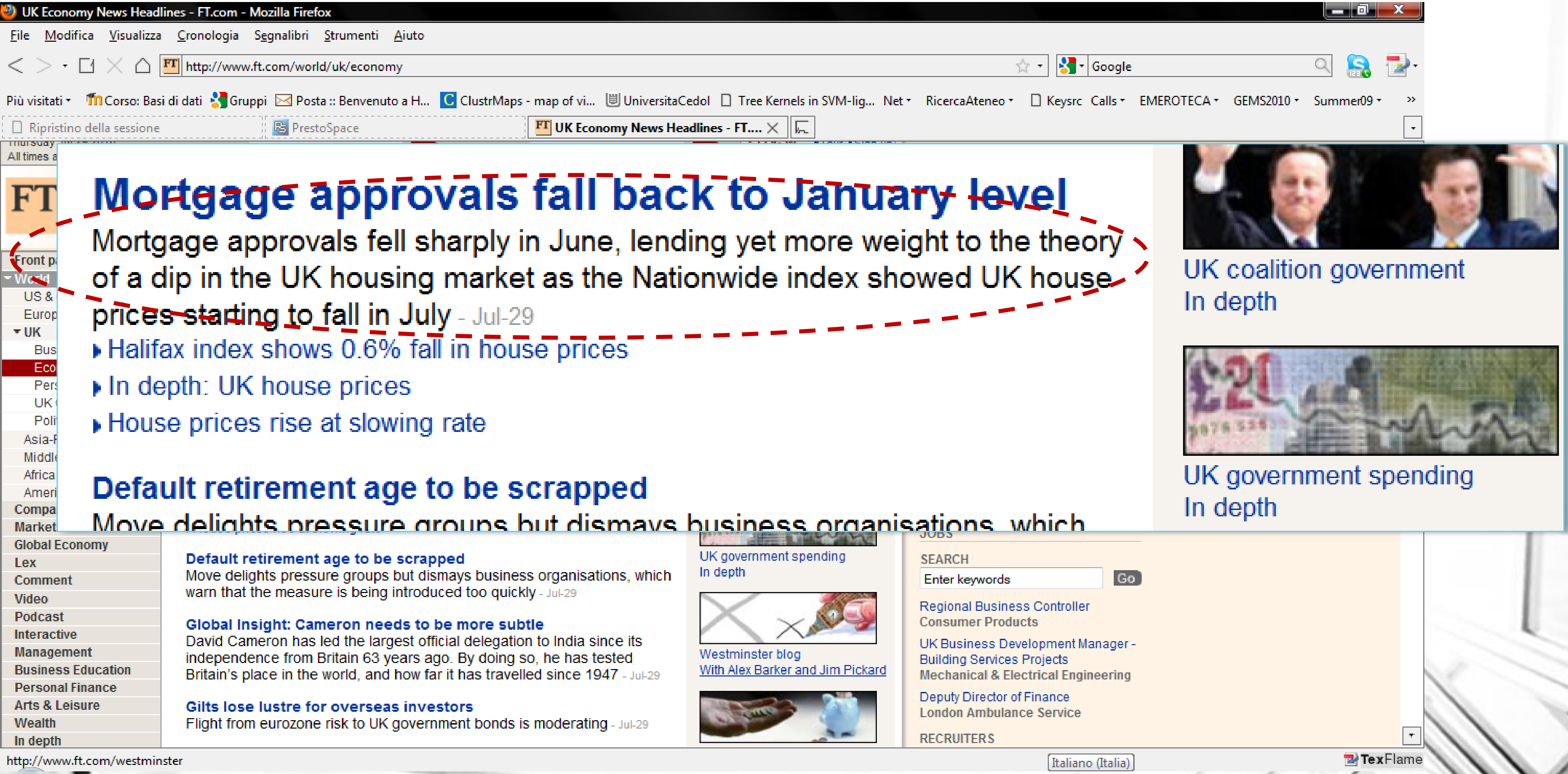

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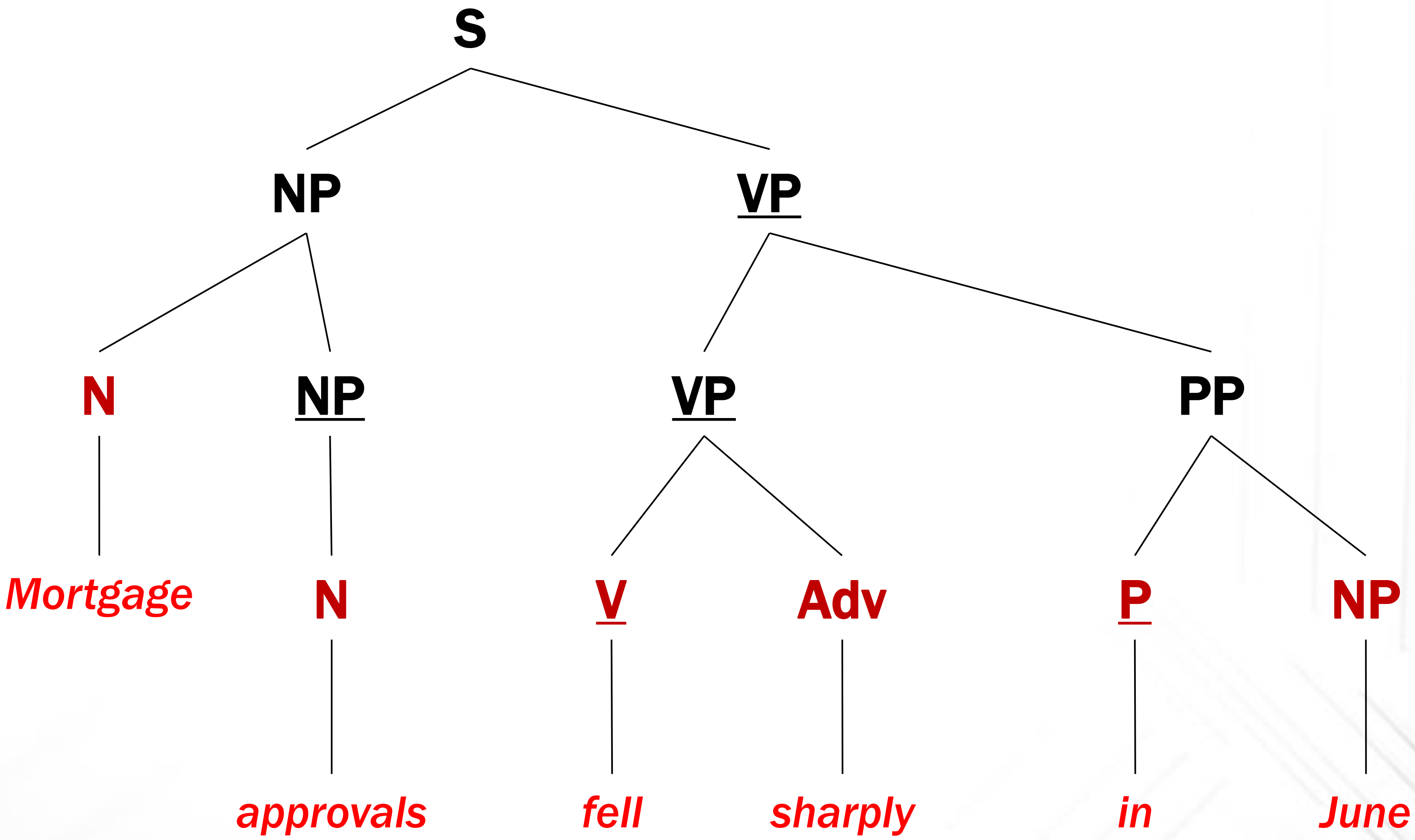

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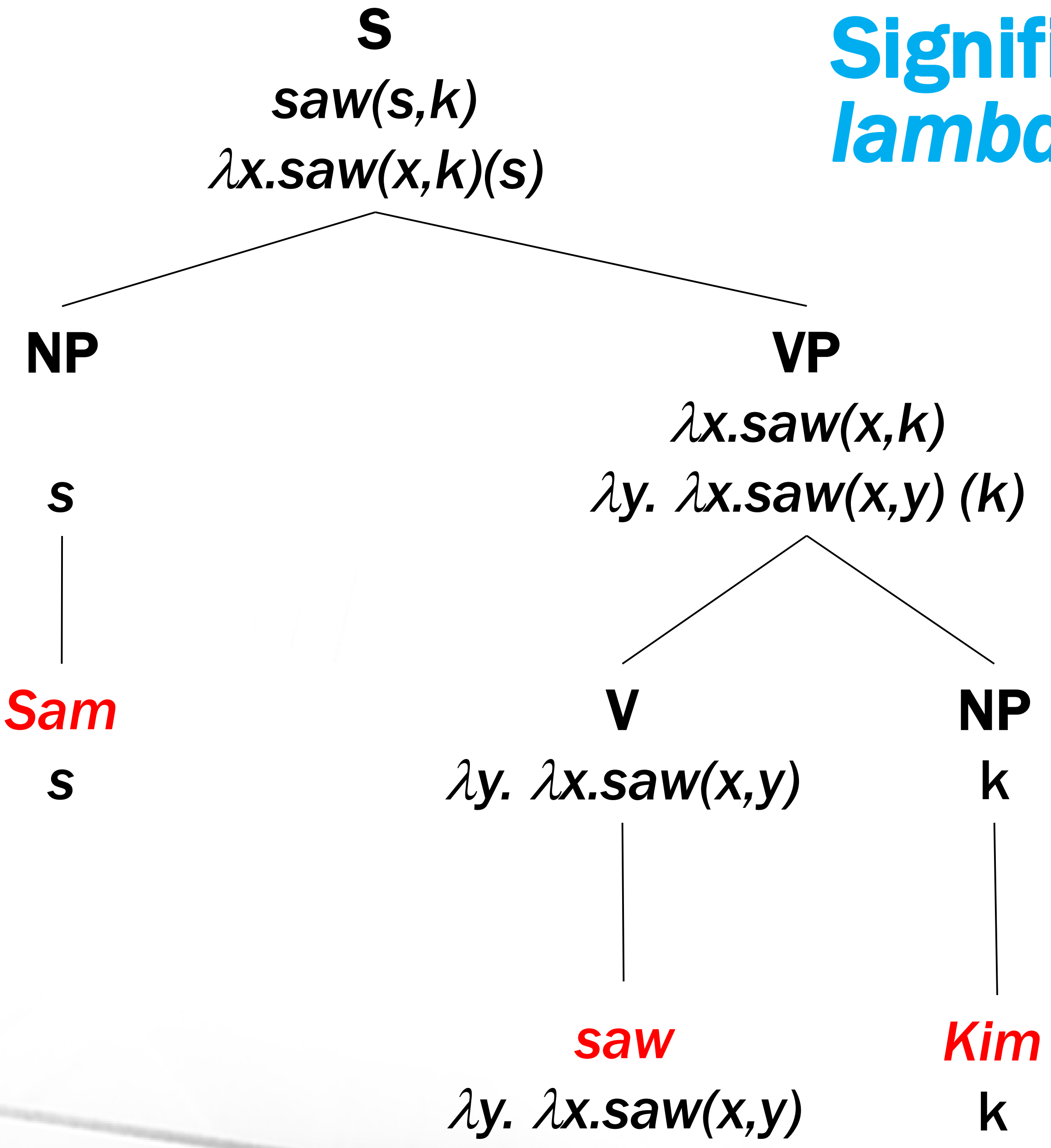
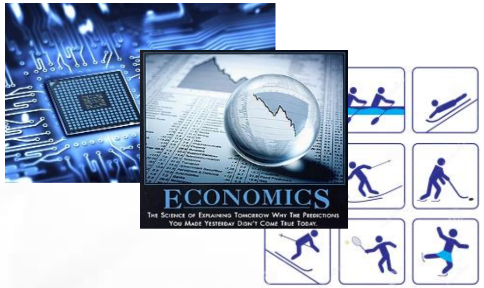


Fenomeni Semantici di interesse

- Entità descritte nei testi (persone, luoghi, organizzazioni, date, espressioni numeriche o monetarie)

- Relazioni / Associazioni tra entità

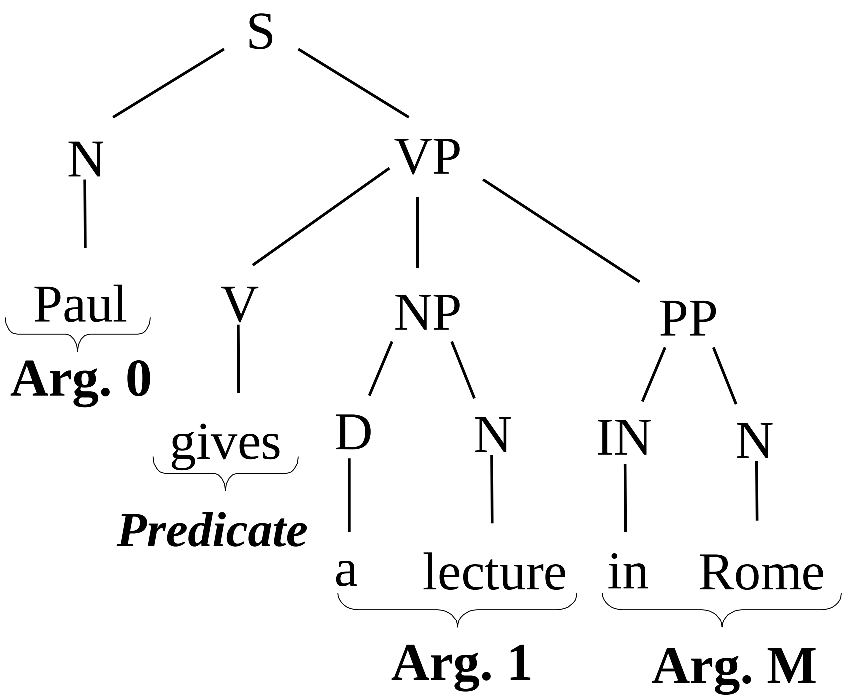
- Fatti ed Eventi



- Temi / Topic / Contesto / Dominio

Predicazione ed Argomenti

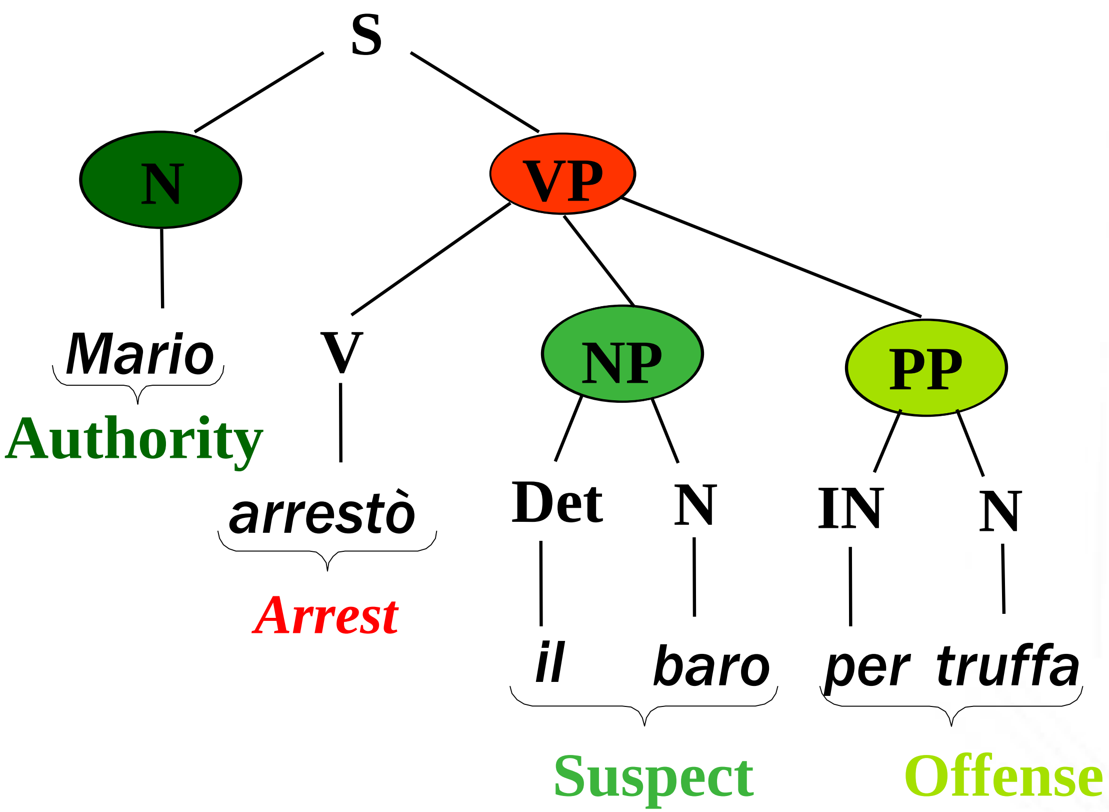
- Il *mapping* sintassi-semantica



Annotazioni Semantiche diverse: PropBank vs. FrameNet

Linking syntax to semantics: Semantic Role Labeling

Mario arrestò il baro per truffa



[Il baro]$_{\text{Suspect}}$ *[fu arrestato]*$_{\text{Arrest}}$ *[da Mario]*$_{\text{Authority}}$ *[per truffa]*$_{\text{Offense}}$

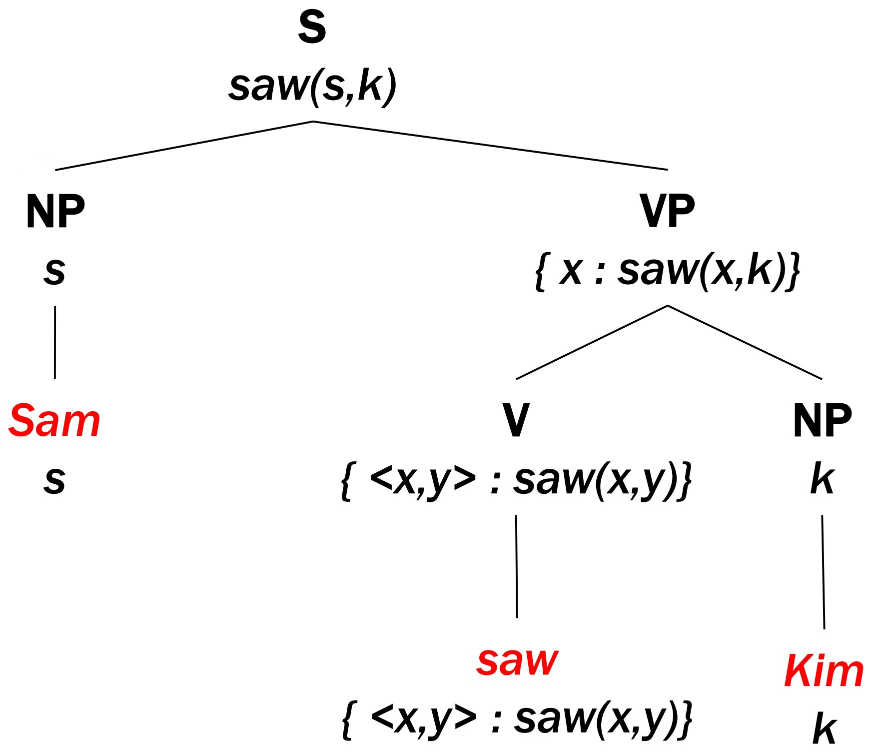
Semantics

- For the sentence:

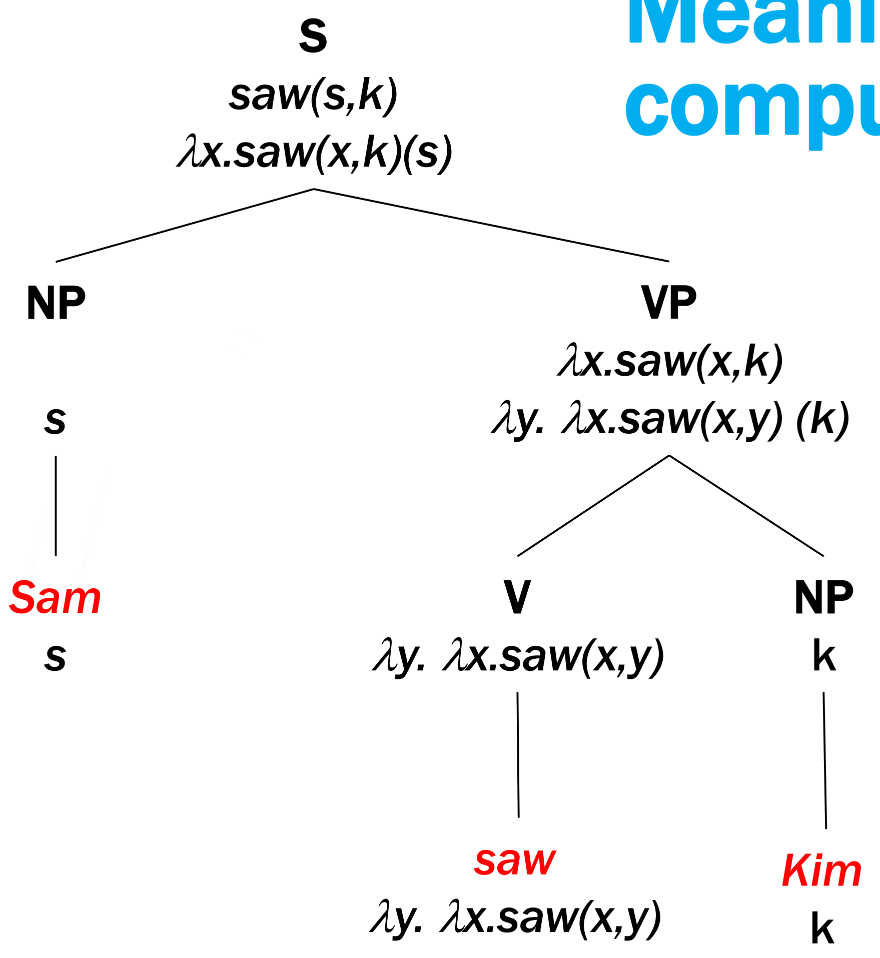
  John saw Kim

- What abut its **meaning?**
- Properties:
  - **It must be derivable compositionally**, i.e. from the meanings of the individual constituents, i.e. ***Kim***, ***John*** and **see**
  - **Independence on syntactic phenomenon**, e.g. *Kim was seen by John*
  - It must **support inferences**
    - *Who was seen by John?*
    - *John saw Kim. He started running to her.*

Truth conditional view on meaning



Meaning as a computation



Syntax and Semantics in textual data

- Compositionality
- The meaning of a complex expression is solely determined by the meanings of its constituent expressions and the rules used to combine them.
- "*I will consider a language to be a set (finite or infinite) of sentences, each finite in length and constructed out of a finite set of elements. All natural languages are languages in this sense. Similarly, the set of "sentences" of some formalized system of mathematics can be considered a language*" Chomsky 1957

Syntax

- In linguistics, **syntax** is the study of the rules that govern the structure of sentences, and which determine their relative grammaticality.
- Such rules govern a number of language phenomena as systems for phonology, morphology, syntax as well as discourse

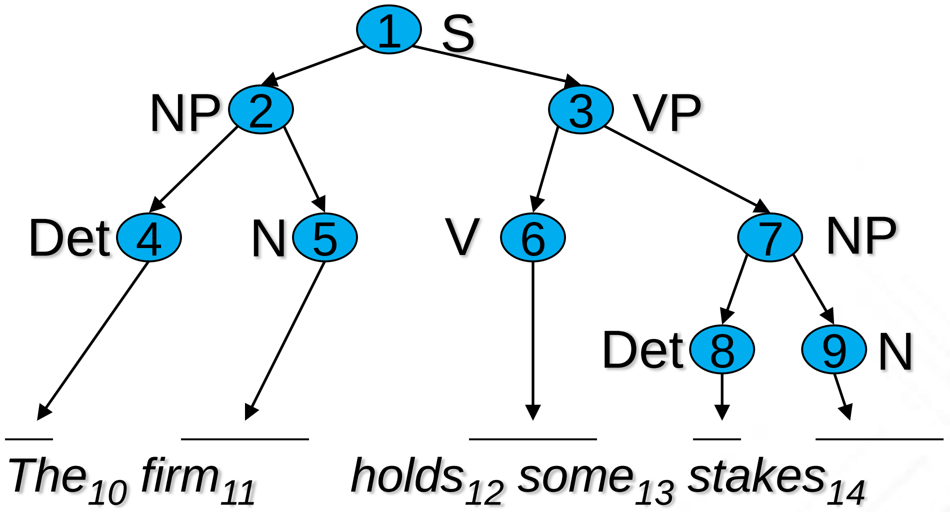
Parse Trees

- The representation of the parsing result is a structure that expresses:
  - The order of constituent elements in the sentence
  - The grammatical type of constituents
  - The hierarchical organization of constitunts
- The structures able to express these properties are the derivation trees also called parse trees

Grammars and Trees

"The firm holds some stakes"

- Vn={S,NP,VP,Det,N},   Axiom: S
- Productions: {S⟶NP VP, VP⟶V NP, NP⟶Det N}
- Derivation:
  - S > NP VP > Det N VP > *The* N VP > *The firm* VP > *The firm* V NP > *The firm holds* NP > *The firm holds* Det N > *The firm holds some* N > *The firm holds some stakes*



Semantics: sense, predicates and arguments

- In the traditional view grammatical categories give rise at the semantic level to 0-arity, unary (e.g. nouns) or n-ary (e.g. verbs) predicates
- Sentence semantics is expressed via quantified logical formulas
- E.g. *John gives mary the book*
- `Give( John, Mary, book)`
- `∃e1,e2,e3:`

```
give(e1, e2, e3) ∧ book(e3) ∧
                        name(e1, John) ∧
                              name(e2, Mary)
```

Semantics

- Words *senses* activates predicates
  - Bank/money vs. bank/river
  - bank_1(X) vs. bank_2(X)
- Verbal predicates express
  - Events/states
  - Relation among participants

- See unit "Ambiguity and Variability in Natural Languages " on the Course Web page
- For a discussion about a Prolog-based approach see "Semantic Analysis in Prolog "

Three Perspectives on Meaning

- Lexical Semantics
  - The meanings of individual words
- Formal Semantics (or Compositional Semantics or Sentential Semantics)
  - How those meanings combine to make meanings for individual sentences or utterances
- Discourse or Pragmatics
  - How those meanings combine with each other and with other facts about various kinds of context to make meanings for a text or discourse
  - Dialog or Conversation is often lumped together with Discourse

Lexical Semantic:
Relationships between word meanings

- Homonymy
- Polysemy
- Synonymy
- Antonymy
- Hypernomy
- Hyponomy
- Meronomy

Homonymy

- **Homonymy:**
  - Lexemes that share a form
    - Phonological, orthographic or both
  - But have unrelated, distinct meanings
  - Clear example:
    - Bat (wooden stick-like thing) vs
    - Bat (flying scary mammal thing)
    - Or bank (financial institution) versus bank (riverside)
  - Can be also homophones, homographs, or both:
    - Homophones:
      - *Write* and *right*
      - *Piece* and *peace*

Polysemy

- The bank is constructed from red brick
  I withdrew the money from the bank
- Are those the same sense?
- Or consider the following WSJ example
  - While some banks furnish sperm only to married women, others are less restrictive

  - Which sense of bank is this?
    - Is it distinct from (homonymous with) the river bank sense?
    - How about the savings bank sense?

Metaphor and Metonymy

- Specific types of polysemy
- Metaphor:
  - Germany will pull Slovenia out of its economic slump.
  - *I spent 2 hours on that homework*.
- Metonymy
  - The White House announced yesterday.
  - This chapter talks about part-of-speech tagging
  - Bank (building) and bank (financial institution)

Synonyms

- Word that have the same meaning in some or all contexts.
  - *filbert / hazelnut*
  - *couch / sofa*
  - *big / large*
  - *automobile / car*
  - *vomit / throw up*
  - *Water / H_2O*
- Two lexemes are synonyms if they can be successfully substituted for each other in all situations
  - If so they have the same **propositional meaning**

Synonyms

- But there are few (or no) examples of perfect synonymy.
  - Why should that be?
  - Even if many aspects of meaning are identical still may not preserve the acceptability based on notions of politeness, slang, register, genre, etc.
- Example:
  - Water and H_2O
  - I would not say

    I like fresh H_2O after the tennis

Some terminology

- Lemmas and wordforms
  - A **lexeme** is an abstract pairing of meaning and form
  - A **lemma** or **citation form** is the grammatical form that is used to represent a **lexeme**.
    - ***Carpet*** is the lemma for ***carpets, Dormir*** is the lemma for ***duermes*.**
  - Specific surface forms *carpets, sung, duermes* are called **wordforms**

- The lemma *bank* has two **senses:**
  - Instead, a **bank** can hold the investments in a custodial account in the client’s name
  - But as agriculture burgeons on the east **bank**, the river will shrink even more.

- A **sense** is a discrete representation of one aspect of the meaning of a word

Synonymy is a relation between senses rather than words

- Consider the words *big* and *large*
- Are they synonyms?
  - How **big** is that plane?
  - Would I be flying on a **large** or small plane?
- How about here:
  - Miss Nelson, for instance, became a kind of **big** sister to Benjamin.
  - ?Miss Nelson, for instance, became a kind of **large** sister to Benjamin.
- Why?
  - *big* has a sense that means being older, or grown up
  - *large* lacks this sense

Antonyms

- Senses that are opposites with respect to one feature of their meaning
- Otherwise, they are very similar!
  - dark / light
  - short / long
  - hot / cold
  - up / down
  - in / out
- More formally: antonyms can
  - define a binary opposition or opposite ends of a scale (*long/short, fast/slow*)
  - Be **reversives**: *rise/fall, up/down*

Hyponymy

- One sense is a **hyponym** of another if the first sense is more specific, denoting a subclass of the other
  - *car* is a hyponym of *vehicle*
  - *dog* is a hyponym of *animal*
  - *mango* is a hyponym of *fruit*
- Conversely
  - *vehicle* is a hypernym/superordinate of *car*
  - *animal* is a hypernym of *dog*
  - *fruit* is a hypernym of *mango*

superordinate	vehicle	fruit	furniture	mammal
hyponym	car	mango	chair	dog

Hypernymy more formally

- Extensional:
  - The class denoted by the superordinate extensionally includes the class denoted by the hyponym
- Entailment:
  - A sense A is a hyponym of sense B if being an A entails being a B
- Hyponymy is usually transitive
  - (A hypo B and B hypo C entails A hypo C)

II. WordNet

- A hierarchically organized lexical database
- On-line thesaurus + aspects of a dictionary
  - Versions for other languages are under development

Category	Unique Forms
Noun	117,097
Verb	11,488
Adjective	22,141
Adverb	4,601

WordNet

- Home page:
  - http://www.cogsci.princeton.edu/cgi-bin/webwn

Format of Wordnet Entries

The noun "bass" has 8 senses in WordNet.

1. bass^1 - (the lowest part of the musical range)
2. bass^2, bass part^1 - (the lowest part in polyphonic music)
3. bass^3, basso^1 - (an adult male singer with the lowest voice)
4. sea bass^1, bass^4 - (the lean flesh of a saltwater fish of the family Serranidae)
5. freshwater bass^1, bass^5 - (any of various North American freshwater fish with lean flesh (especially of the genus Micropterus))
6. bass^6, bass voice^1, basso^2 - (the lowest adult male singing voice)
7. bass^7 - (the member with the lowest range of a family of musical instruments)
8. bass^8 - (nontechnical name for any of numerous edible marine and freshwater spiny-finned fishes)

The adjective "bass" has 1 sense in WordNet.

1. bass^1, deep^6 - (having or denoting a low vocal or instrumental range) *"a deep voice"; "a bass voice is lower than a baritone voice"; "a bass clarinet"*

WordNet Noun Relations

Relation	Also called	Definition	Example
Hypernym	Superordinate	From concepts to superordinates	$breakfast^1 \rightarrow meal^1$
Hyponym	Subordinate	From concepts to subtypes	$meal^1 \rightarrow lunch^1$
Member Meronym	Has-Member	From groups to their members	$faculty^2 \rightarrow professor^1$
Has-Instance		From concepts to instances of the concept	$composer^1 \rightarrow Bach^1$
Instance		From instances to their concepts	$Austen^1 \rightarrow author^1$
Member Holonym	Member-Of	From members to their groups	$copilot^1 \rightarrow crew^1$
Part Meronym	Has-Part	From wholes to parts	$table^2 \rightarrow leg^3$
Part Holonym	Part-Of	From parts to wholes	$course^7 \rightarrow meal^1$
Antonym		Opposites	$leader^1 \rightarrow follower^1$

WordNet Verb Relations

Relation	Definition	Example
Hypernym	From events to superordinate events	$fly^9 \rightarrow travel^5$
Troponym	From a verb (event) to a specific manner elaboration of that verb	$walk^1 \rightarrow stroll^1$
Entails	From verbs (events) to the verbs (events) they entail	$snore^1 \rightarrow sleep^1$
Antonym	Opposites	$increase^1 \Longleftrightarrow decrease^1$

WordNet Hierarchies

```
Sense 3
bass, basso --
(an adult male singer with the lowest voice)
=> singer, vocalist, vocalizer, vocaliser
   => musician, instrumentalist, player
      => performer, performing artist
         => entertainer
            => person, individual, someone...
               => organism, being
                  => living thing, animate thing,
                     => whole, unit
                        => object, physical object
                           => physical entity
                              => entity
               => causal agent, cause, causal agency
                  => physical entity
                     => entity

Sense 7
bass --
(the member with the lowest range of a family of
musical instruments)
=> musical instrument, instrument
   => device
      => instrumentality, instrumentation
         => artifact, artefact
            => whole, unit
               => object, physical object
                  => physical entity
                     => entity
```

How is “*sense*” defined in WordNet?

- The set of near-synonyms for a WordNet sense is called a **synset** (**synonym set**); it’s their version of a sense or a concept
- Example: **chump** as a noun to mean
  - ‘a person who is gullible and easy to take advantage of’

{chump^1, fool^2, gull^1, mark^9, patsy^1, fall guy^1, sucker^1, soft touch^1, mug^2}

- Each of these senses share this same gloss
- Thus for WordNet, the meaning of this sense of **chump** *is* this list.

Word Similarity

- Synonymy is a binary relation
  - Two words are either synonymous or not
- We want a looser metric
  - Word similarity or
  - Word distance
- Two words are more similar
  - If they share more features of meaning

Word Similarity

- Actually these are really relations between **senses**:
  - Instead of saying "*bank is like fund*"
  - We say
    - Bank1 *is similar to* fund3
    - Bank2 *is similar to* slope5
- Similarity are computed over both words and senses

Why word similarity

- Spell Checking
- Information retrieval
- Question answering
- Machine translation
- Natural language generation
- Language modeling
- Automatic essay grading

Syntactic Argument Structures

- (Verbal) Relations require a fixed number of participants, called arguments
- The syntactic structure predicts the number and type of arguments through subcategorization frames
  - (Bob (gave (Mary) (the book) (on Monday)))
  - (Bob (gave (the book) (to Mary) (on Monday)))

Thematic roles

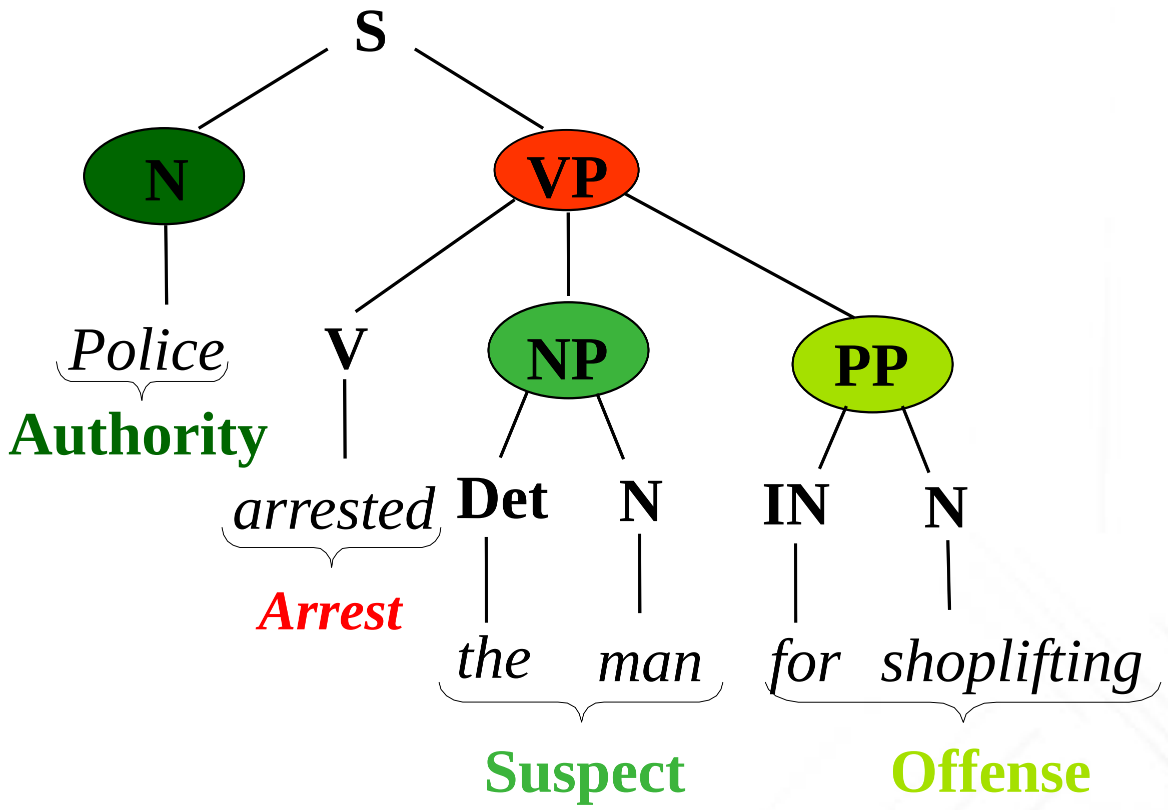
- Arguments play specific roles, called thematic roles, depending on the predicate but invariant across different syntactic structures giving rise to predicate argument structures
  - `give(Agent:` *Bob*, `Theme:` *the_book*, `Recipient:` *Mary*`)`

- Thematic roles of individual arguments <u>are indexed</u> by their predicates

- *General* and *lexicalized* roles have been introduced

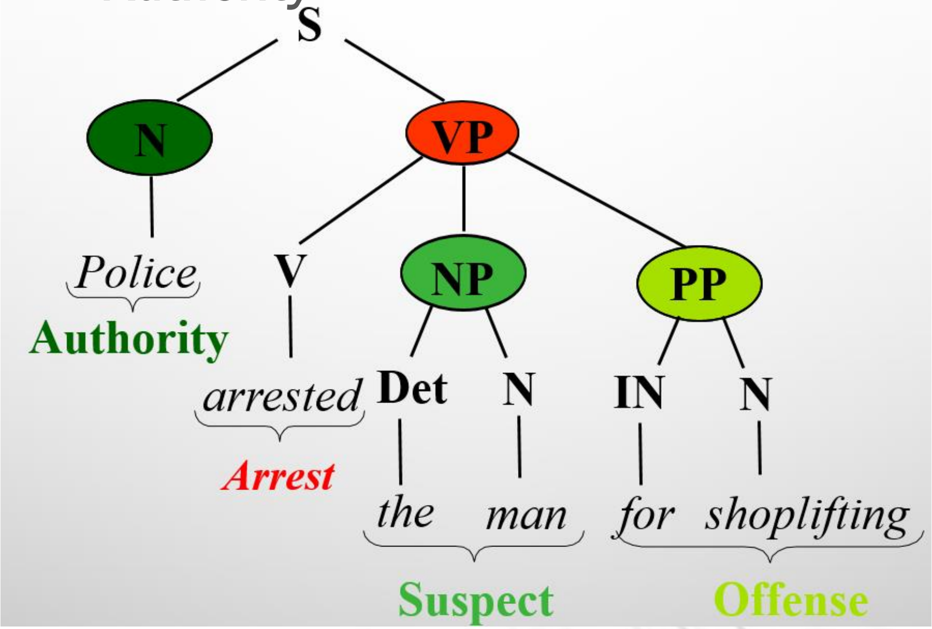
Linking syntax to semantics

- *Police arrested the man for shoplifting*



A tabular vision

Word	Predicate	Semantic Role
Police	-	Authority
arrested	Target	Arrest
the	-	SUSPECT
man	-	SUSPECT
for	-	OFFENSE
Shoplifting	-	OFFENSE



Semantics in NLP: Resources

- Lexicalized Models
  - Propbank
  - NomBank
- Framenet
  - Inspired by frame semantics
  - Frames are lexicalized prototoypes for real -world situations
  - Participants are called frame elements (roles)

Frame Semantics

- Research in Empirical Semantics suggests that **words represents categories of experience** (*situations*)
- A ***frame*** is a cognitive structuring device (i.e. a kind of prototype) indexed by *words* and used to support understanding (Fillmore, 1975)
  - *Lexical Units* **evoke** a Frame in a sentence
- Frames are made of *elements* that express participants to the situation (*Frame Elements*)
- During communication LUs evoke the frames

Fram

Frame: KILLING		
A KILLER or CAUSE causes the death of the VICTIM.		
Frame Elements	KILLER	**John** drowned Martha.
	VICTIM	John drowned **Martha**.
	MEANS	The flood exterminated the rats **by cutting off access to food**.
	CAUSE	**The rockslide** killed nearly half of the climbers.
	INSTRUMENT	It's difficult to suicide **with only a pocketknife**.
Predicates	annihilate.v, annihilation.n, asphyxiate.v,assassin.n, assassinate.v, assassination.n, behead.v, beheading.n, blood-bath.n, butcher.v, butchery.n, carnage.n, crucifixion.n, crucify.v, deadly.a, decapitate.v, decapitation.n, destroy.v, dispatch.v, drown.v, eliminate.v, euthanasia.n, euthanize.v, …	

Frame Semantics

- Lexical descriptions are expected to define the indexed frame and the frame elements with their realization at the syntactic level:
  - *John bought a computer from Janice for 1000 $*
- Mapping into syntactic arguments
  - the buyer is (usually) in the subject position
- Obligatory vs. optional arguments
- Selectional preferences
  - The seller and the buyer are usually “humans” or “social groups”

The FrameNet project

- The aims
  - Create a lexical resource by describing a significant portion of English in terms of precise and rich frame semantics
- The output
  - Frame Database: a structured system of Frames and Fes
  - Lexical database: syntactic and semantic descriptions of frame-evoking words (N,V,A)
  - Annotated Corpus: wide coverage examples

FrameReport - Mozilla Firefox

Frame Report (recent data)

| Top of Frame Index | Top of Lexical Unit Index |

Committing_crime

Definition:

A Perpetrator (generally intentionally) commits a Crime, i.e. does something not permitted by the laws of society.

They PERPETRATED a felony by substituting a lie for negotiations.

The suspect had allegedly COMMITTED the crime to gain the attention of a female celebrity.

FEs:

Core:

Crime [Cr] An act, generally intentional, that has been formally forbidden by law.

How can he COMMIT treason against the King of England in a foreign country , if he is not English?

He PERPETRATED a crime against mother nature.

Perpetrator [Perp] The individual that commits a Crime.

How can he COMMIT treason against the King of England in a foreign country , if he is not English?

He PERPETRATED a crime against mother nature.

Non-Core:

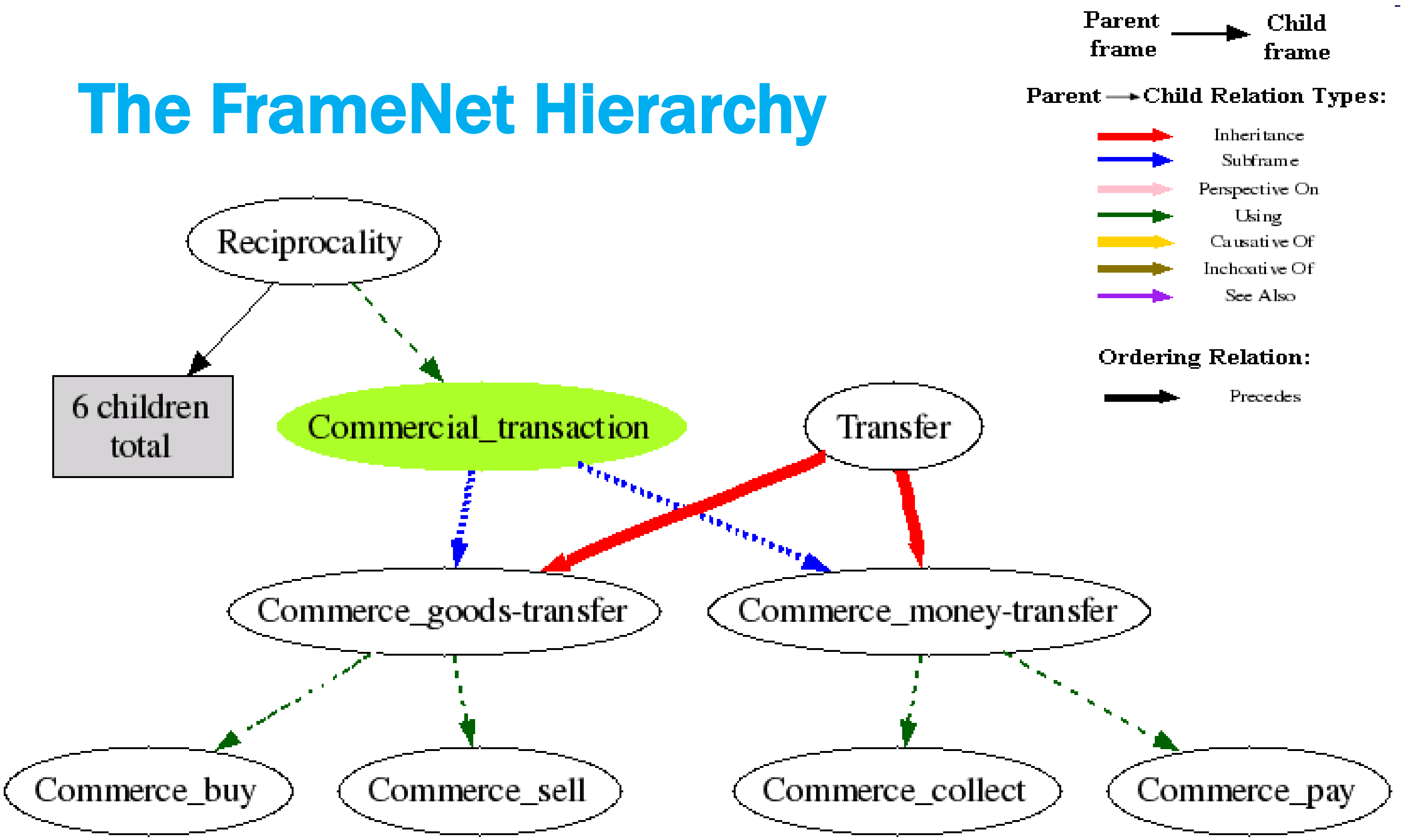
Frequency [Freq] The frequency with which a Crime is committed.

The average serial killer COMMITS a crime every five years.

Instrument [Inst] The Instrument used in committing the crime.

Most crimes are COMMITTED with a firearm.

The FrameNet Hierarchy



Framenet - Data

- Methodology of constructing FrameNet
  - Define/discover/describe frames
  - Decide the participants (frame elements)
  - List lexical units that evoke the frame
  - Find example sentences in the BNC and annotate them
- Corpora
  - FrameNet I -British National Corpus only
  - FrameNet II -LDC North American Newswire corpora
- Size
  - >10,000 lexical units, >825 frames, >135,000 sentences
- http://framenet.icsi.berkeley.edu

Using Framenet

- See later in the slides: Semantic Role Labeling

Overview

- Intelligenza Artificiale e Lingue parlate e scritte
    - Informazioni e Rappresentazioni coinvolte
    - Sfide (ri)correnti, battaglie (già) vinte e rischi inerenti …
- Elaborazione Automatica delle Lingue: Modelli, Metodi e *Risultati*
- break

- Ruolo delle Tecnologie dell'Apprendimento ed Applicazioni:
    - Sviluppo Automatico di Dizionari, Lessici Semantici ed Ontologie
    - Trattamento Semantico della Documentazione Investigativa
    - Sistemi Web-based di Opinion Mining, Market Watch & Brand Reputation Management

Overview

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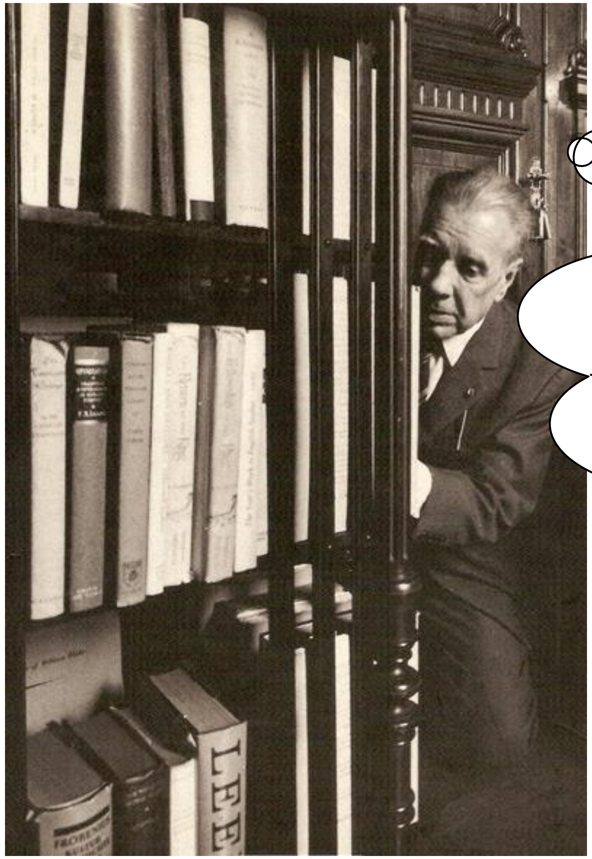
Il Linguaggio come sistema di regole



*… comincia qui la mia disperazione di scrittore. Ogni **linguaggio** è **un alfabeto di simboli** il cui uso presuppone **un passato che gli interlocutori condividono; come trasmettere agli altri l’infinito Aleph** che la mia timorosa memoria a stento abbraccia?*

(*) J.L.Borges, “*L’aleph*”, 1949.

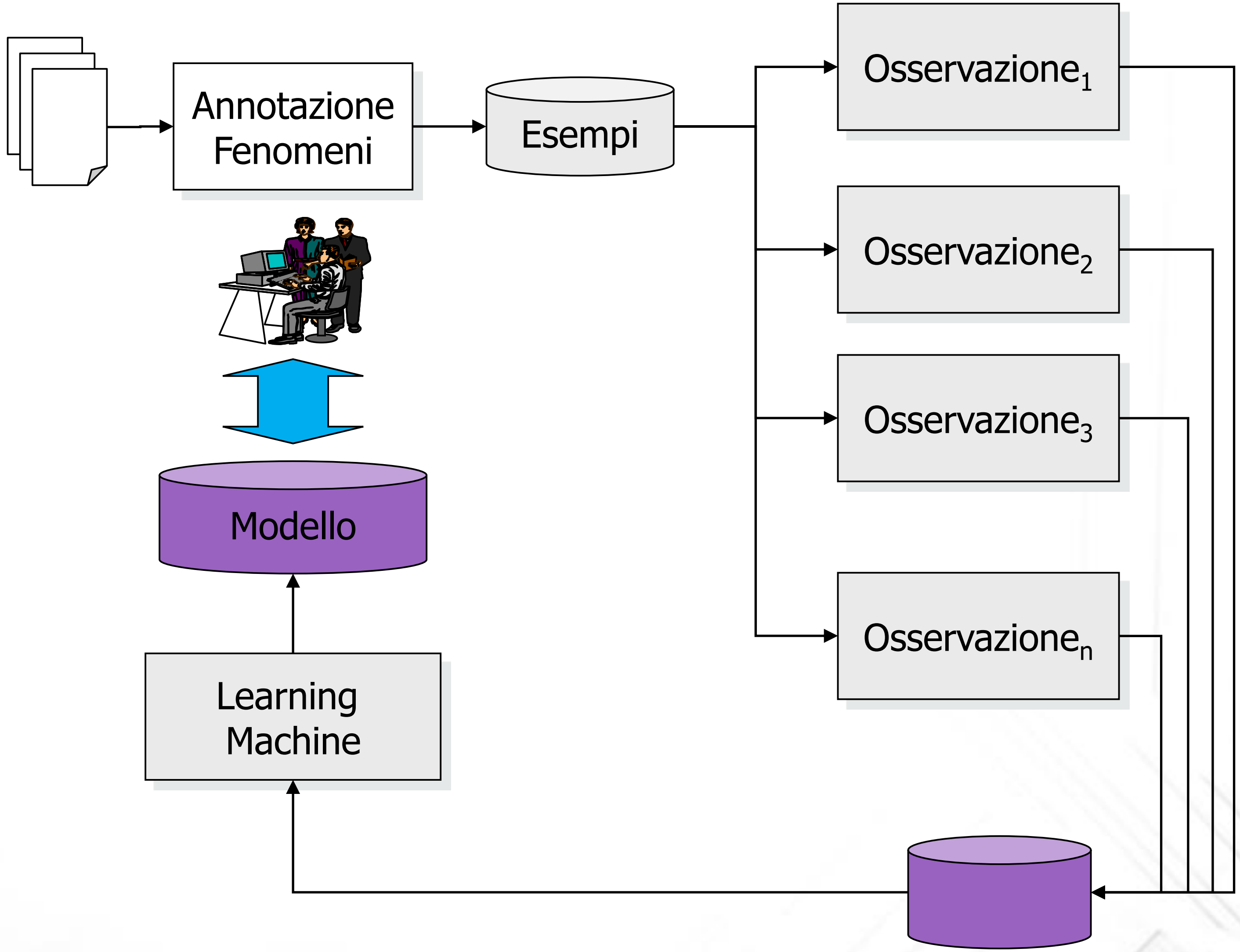
- … Il significato può essere appreso e riconosciuto nelle prassi del suo uso quotidiano
  - *The meaning of a word is to be defined by the rules for its use, not by the feeling that attaches to the words*
    L. Wittgenstein's Lectures, Cambridge 1932-1935.

- Riconoscere un significato consiste nel mappare un testo ad una esperienza (prassi) attraverso meccanismi quali **la analogia** o la approssimazione di **funzioni di equivalenza** o la **minimizzazione del rischio di sbagliare**

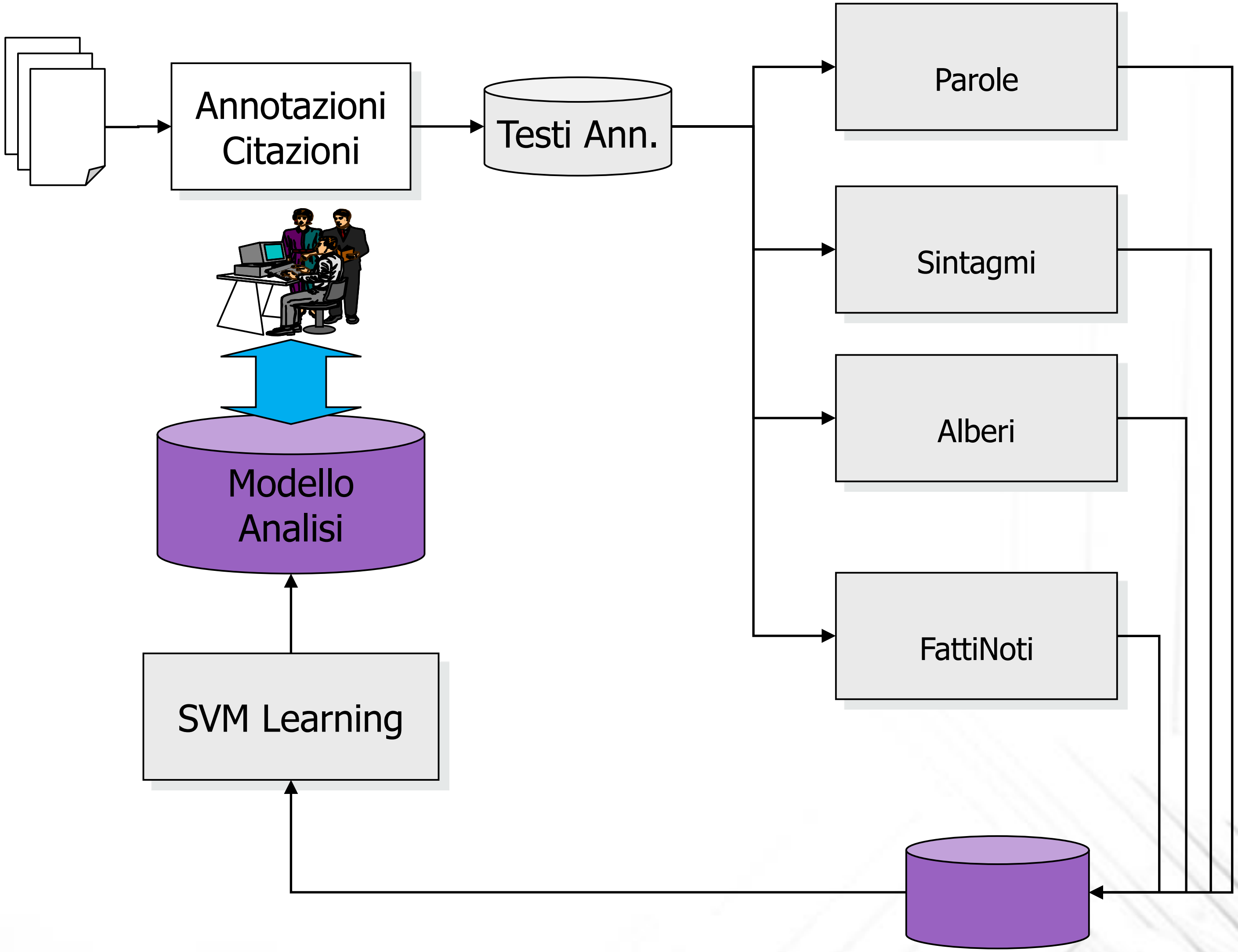
- L'intepretazione si trasforma dunque nella ***induzione di una funzione di decisione a partire dall'esperienza***

Una prospettiva differente

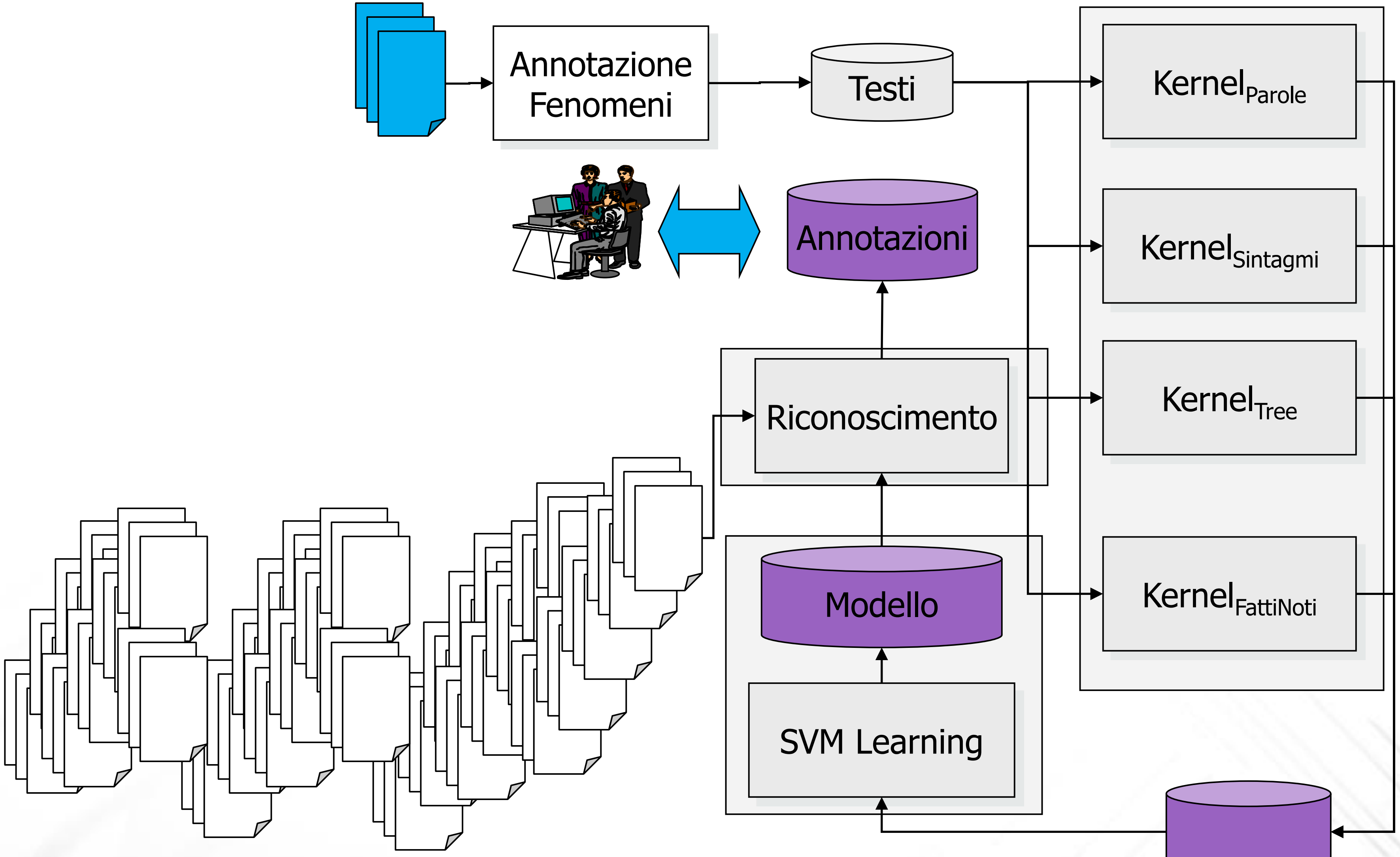
Un Processo Induttivo



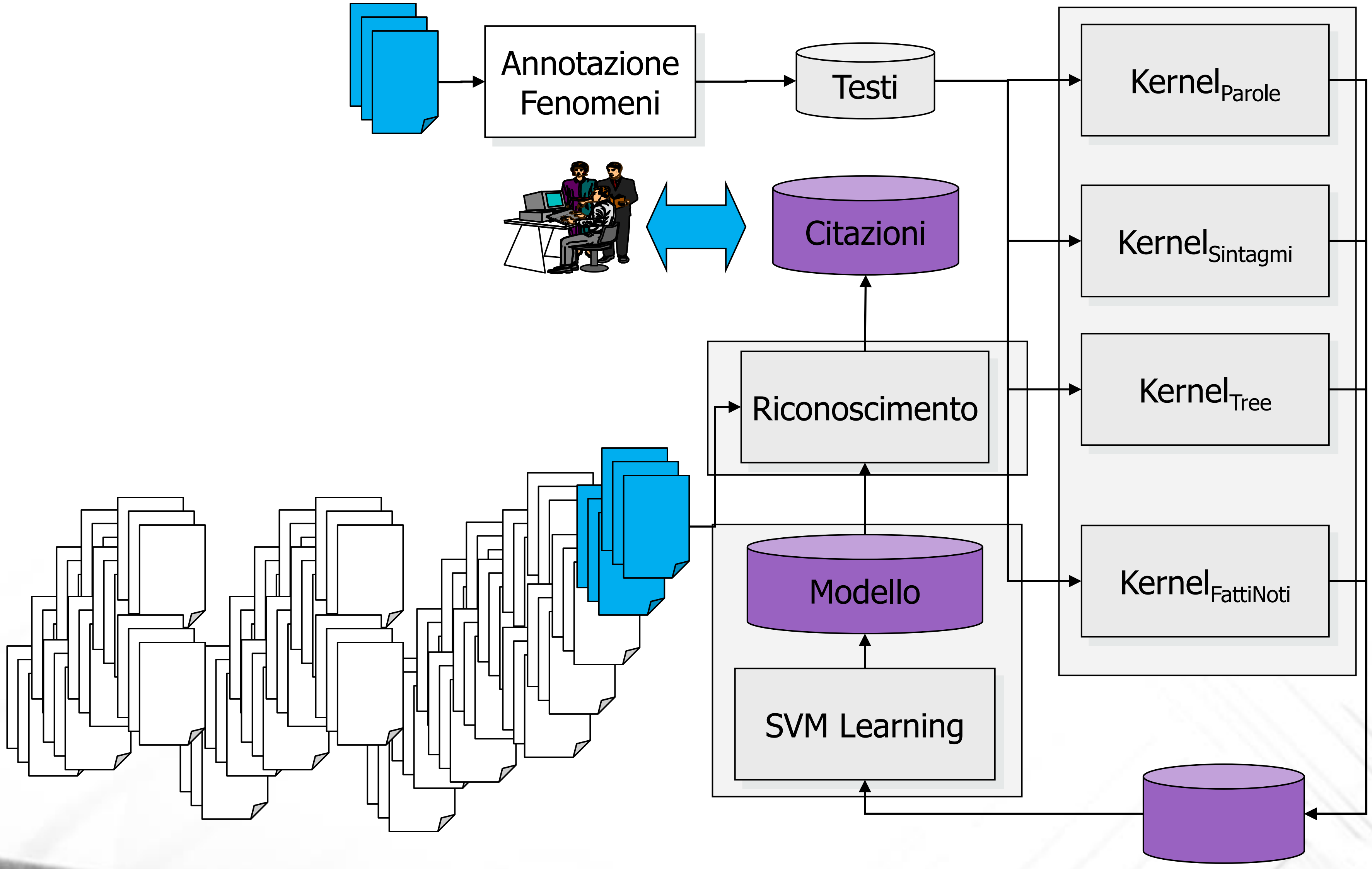
Il Processo Induttivo



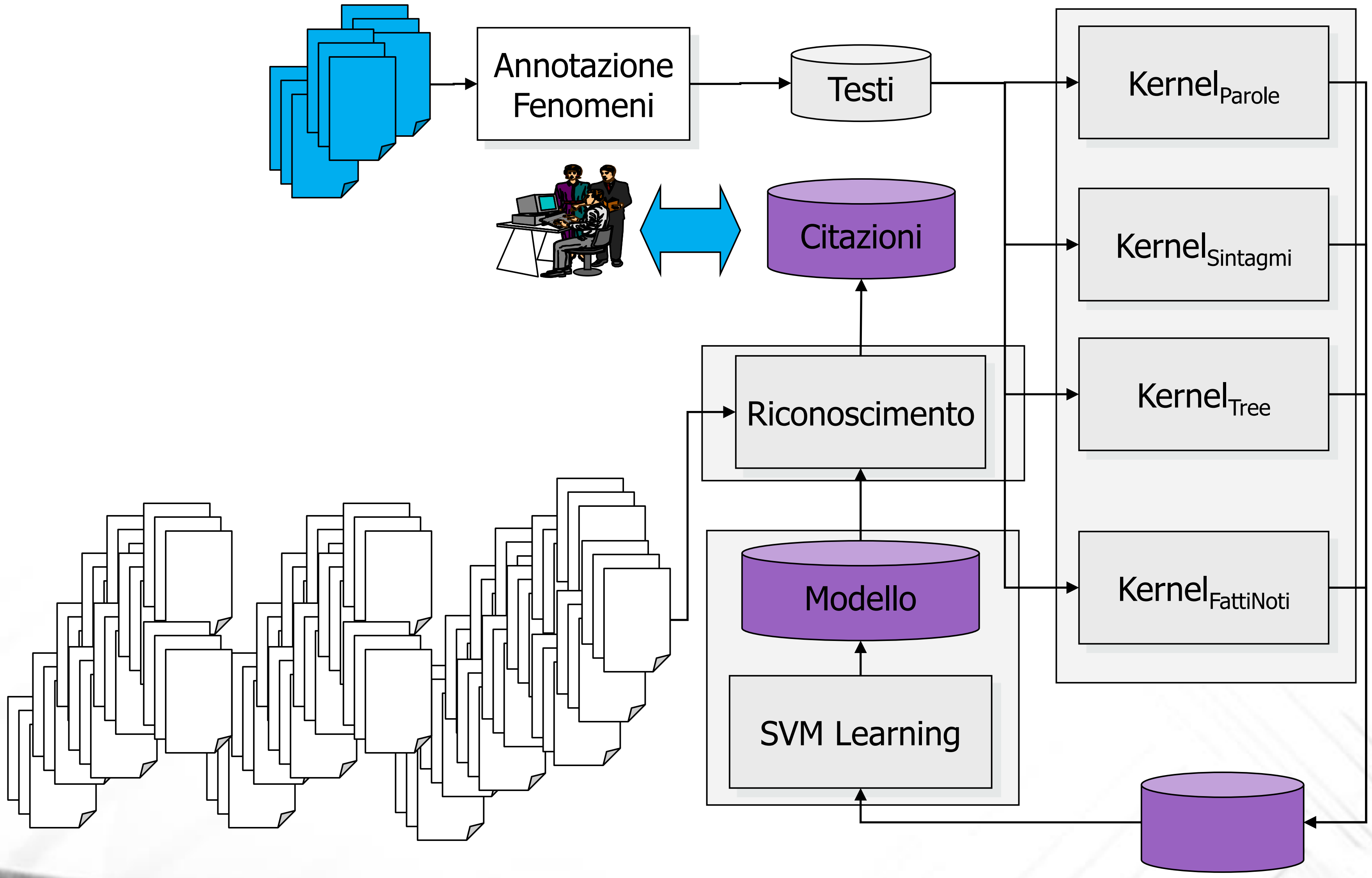
Supporto alla Analisi dei Dati



Supporto alla Analisi dei Dati



Supporto alla Analisi dei Dati



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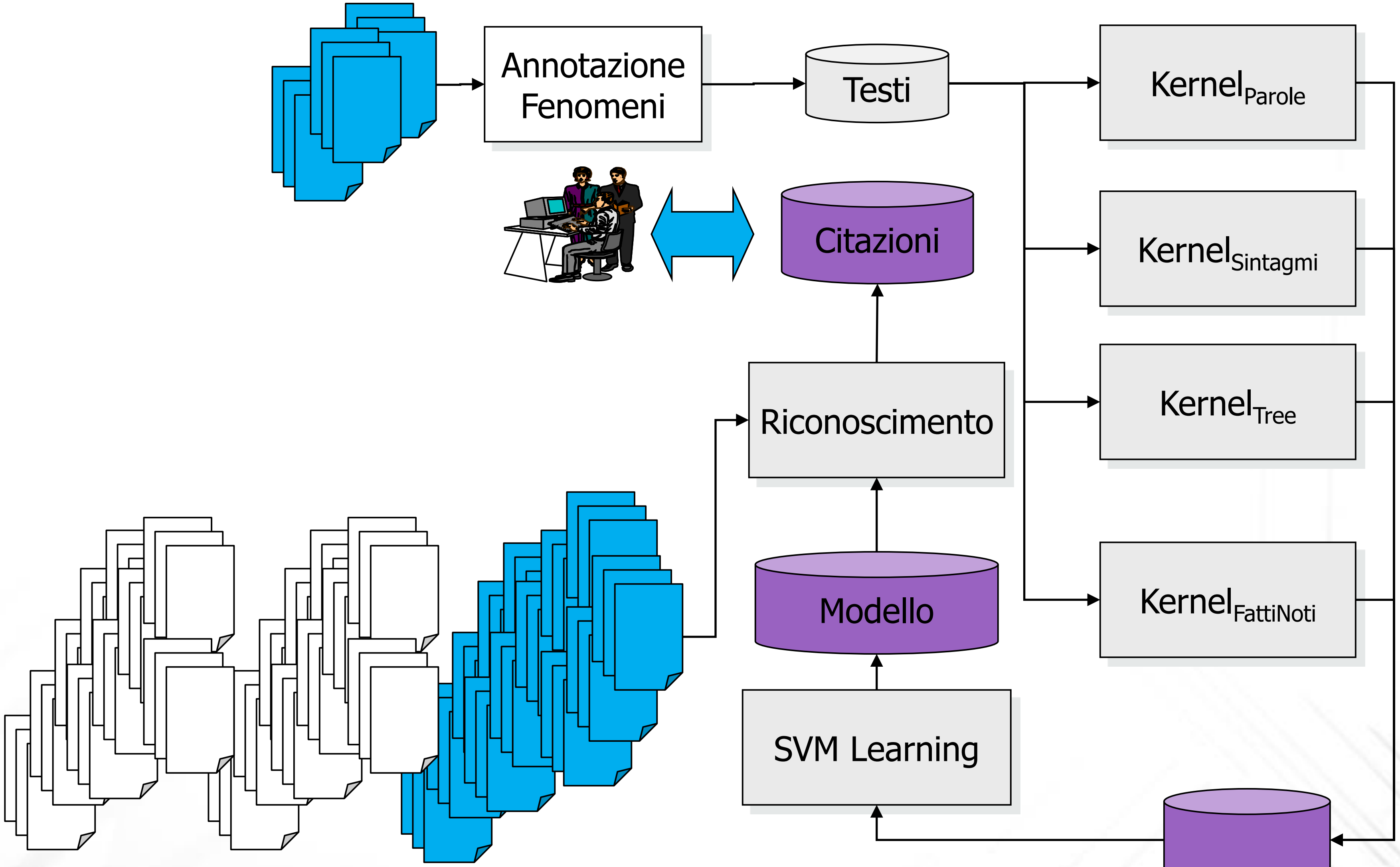

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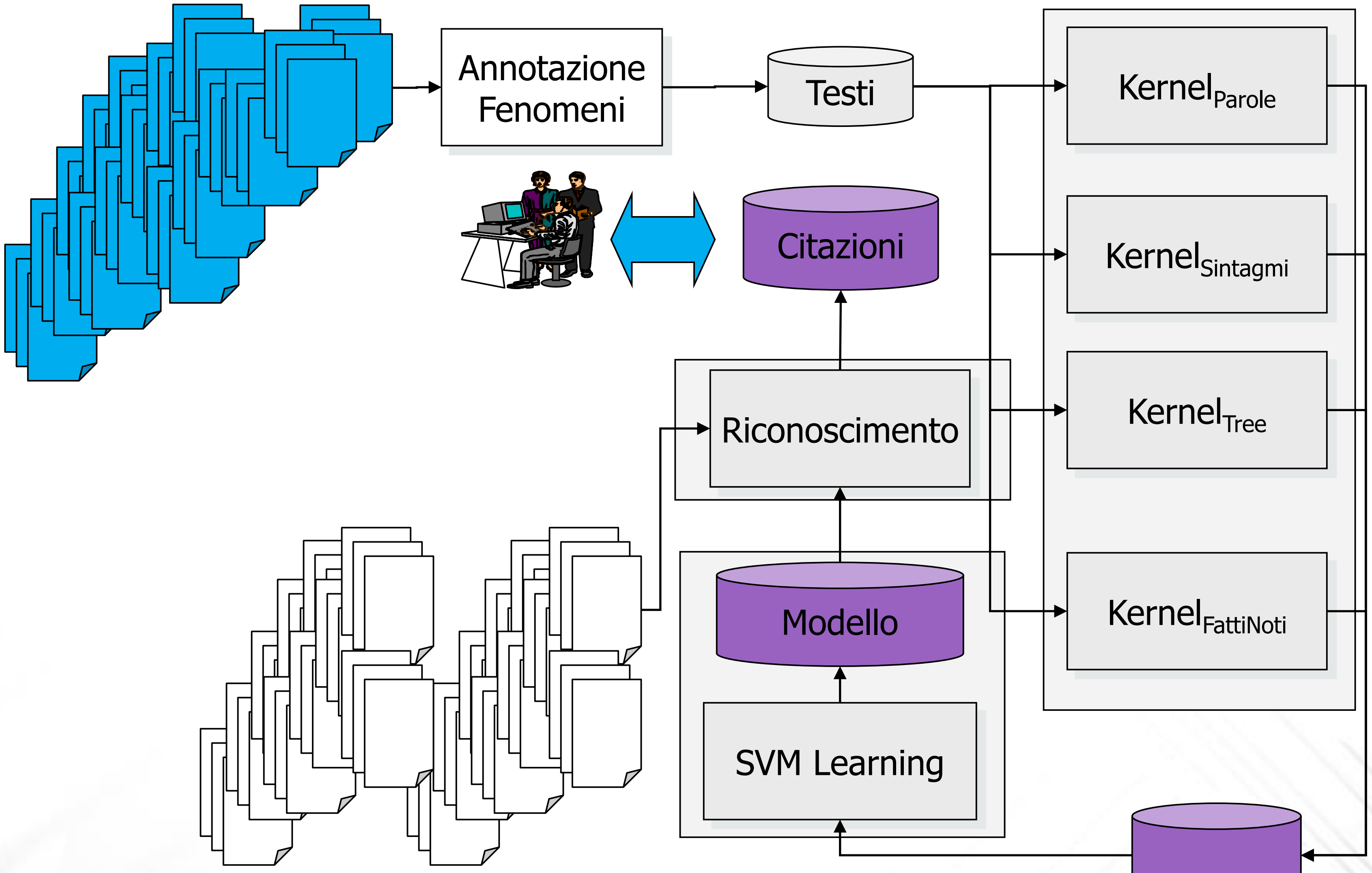
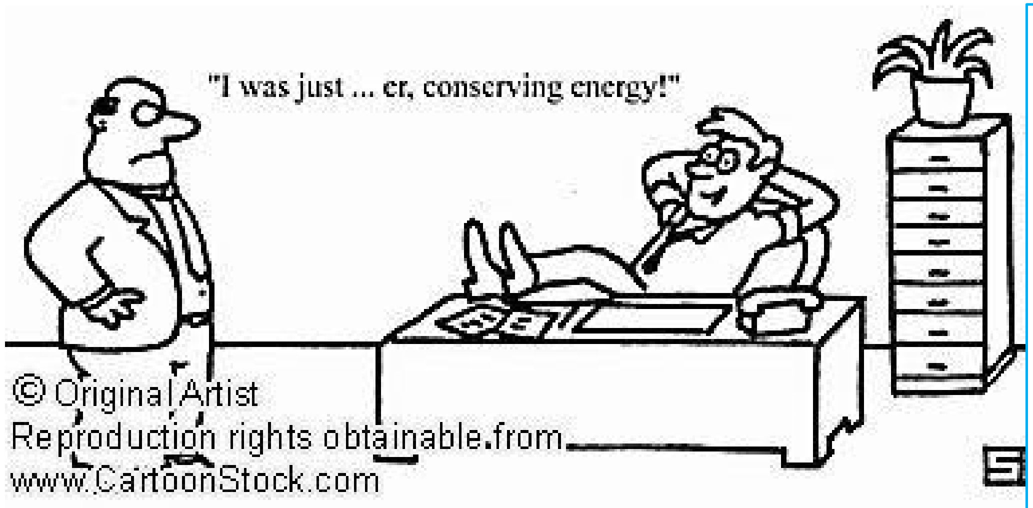


Tecnologie D*ata-driven* : Benefici



- Disponibilità di algoritmi molto **accurati** ed **efficienti**
- L'apprendimento è **portabile** mentre programmare i modelli è dipendente dal **task** (i.e. scenario)
- **Soluzioni ad alta qualità** possono essere ottenute in modo **cost-effective**
- **Raccogliere esempi** è più semplice e coinvolge **profili professionali meno specializzati**
- **L'analisi di larga scala** è resa possibile

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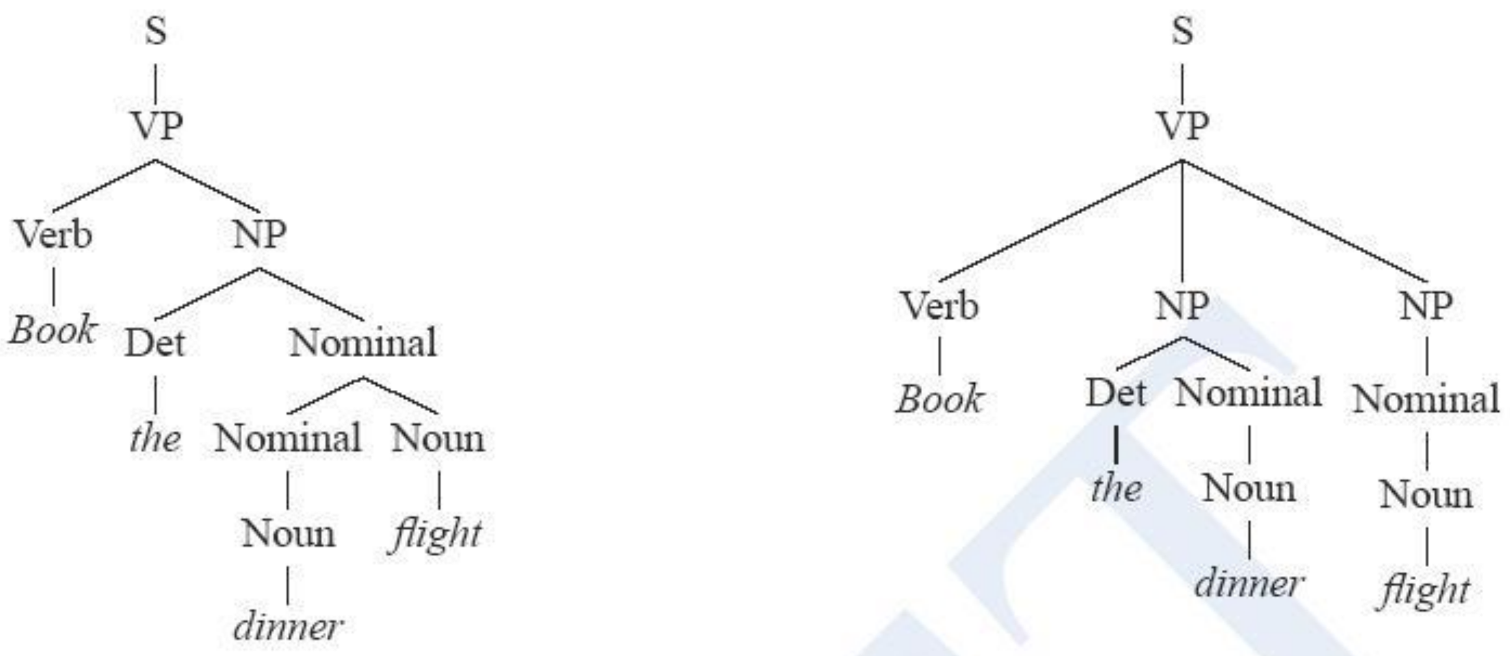
Machine Learning in NLP

- Lexical Semantics:
  - Acquisition of lexical semantic dictionaries from corpora (aka distributional semantic methods, word spaces and embeddings)
  - Word Sense Disambiguation
- Data-driven Computational Semantics
  - Named Entity Recognition and Relation Extraction
  - Shallow Semantic Parsing (aka Semantic Role Labeling)
- NLP for Information Retrieval tasks
  - Semantic Indexing
  - (Open domain) Question Answering
  - Opinion Analysis
  - Community detection and Reccommeding

Le armi del Machine Learning

- Apprendimento di Regole e Pattern sui Dati
  - Frequent Pattern Mining (Basket analysis)
- Estensioni Probabilistiche delle Grammatiche
  - Probabilstic CFGs
  - Grammatiche Stocastiche
- Apprendimento Discriminativo nelle reti neurali
- SVM: percettroni
  - Funzioni Kernel in Spazi impliciti
- Modelli Bayesiani e Grafici



Rules			P
S	→	VP	.05
VP	→	Verb NP	.20
NP	→	Det Nominal	.20
Nominal	→	Nominal Noun	.20
Nominal	→	Noun	.75
Verb	→	book	.30
Det	→	the	.60
Noun	→	dinner	.10
Noun	→	flights	.40

Rules			P
S	→	VP	.05
VP	→	Verb NP NP	.10
NP	→	Det Nominal	.20
NP	→	Nominal	.15
Nominal	→	Noun	.75
Nominal	→	Noun	.75
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Noun	→	dinner	.10
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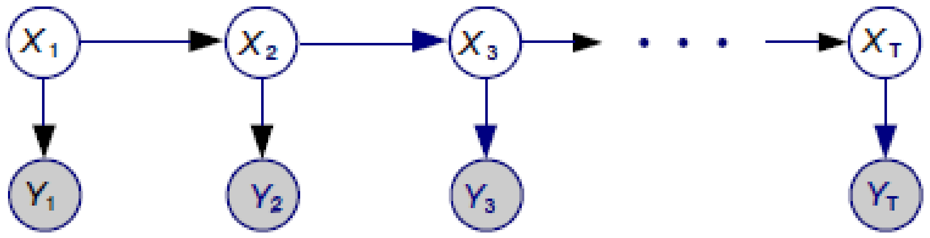
Figure 13.2 Two parse trees for an ambiguous sentence. The transitive parse (a) cor-

Hidden Markov Models (HMM)

- Stati = Categorie/Concetti/Proprietà
- Osservazioni



- Emissioni

$$p(X_{1,\ldots,T}, Y_{1,\ldots,T}) = p(X_1)p(Y_1|X_1)\prod_{t=2}^{T}\left[p(X_t|X_{t-1})p(Y_t|X_t)\right]$$

- Transizioni

- Applicazioni:
  - Riconoscimento Vocale
  - Etichettatura Grammaticale (*POS tagging*)

Apprendimento Discriminativo

- Tipico delle reti neurali sin dalle prime proposte della Cibernetica (Minsky&Papert, 1956)
- Basato sulla nozione geometrica di prodotto interno e quindi di spazio vettoriale metrico
- Support Vector Machines (ma anche altri On-line Learning algorithms)
  - Kernels
  - Pre-training methods through word spaces and embeddings
  - Markovian SVMs for sequence labeling tasks
    - (SVM-HMM) come ibridazione di un modello discriminativo (SVM locali ai singoli time stamp) e di un approccio generativo (HMM per l'intera sequenza)

Named Entity Recognition

- See the Kozareva tutorial at: http://www.isi.edu/natural-language/teaching/cs544/spring11/kozareva_lecture3.ppt
- Continue ...

Semantic Role Labeling

- The Task
  - From Syntactic Argument Structures to Thematic Roles
  - SRL as a classification task
- SRL: Reference Linguistic Theories and Resources
- An SRL architecture
- Experiments and Results
  - Early models
  - SPTK (Croce et al., 2011)

Syntactic Argument Structures

- (Verbal) Relations require a fixed number of participants, called arguments
- The syntactic structure predicts the number and type of arguments through subcategorization frames
  - (Bob (gave (Mary) (the book) (on Monday)))
  - (Bob (gave (the book) (to Mary) (on Monday)))

Thematic roles

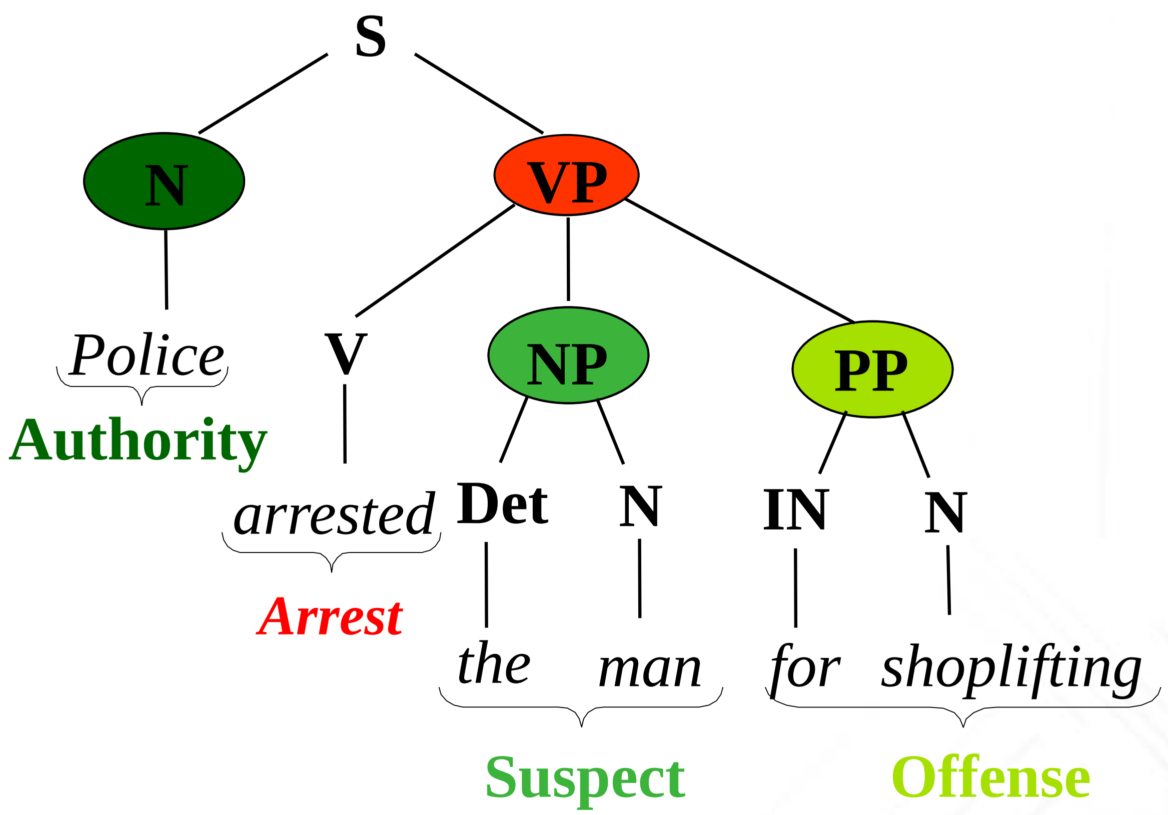
- Arguments play specific roles, called thematic roles, depending on the predicate but invariant across different syntactic structures giving rise to predicate argument structures
  - `give(Agent:` *Bob*, `Theme:` *the_book*, `Recipient:` *Mary*`)`

- Thematic roles of individual arguments <u>are indexed</u> by their predicates

- *General* and *lexicalized* roles have been introduced

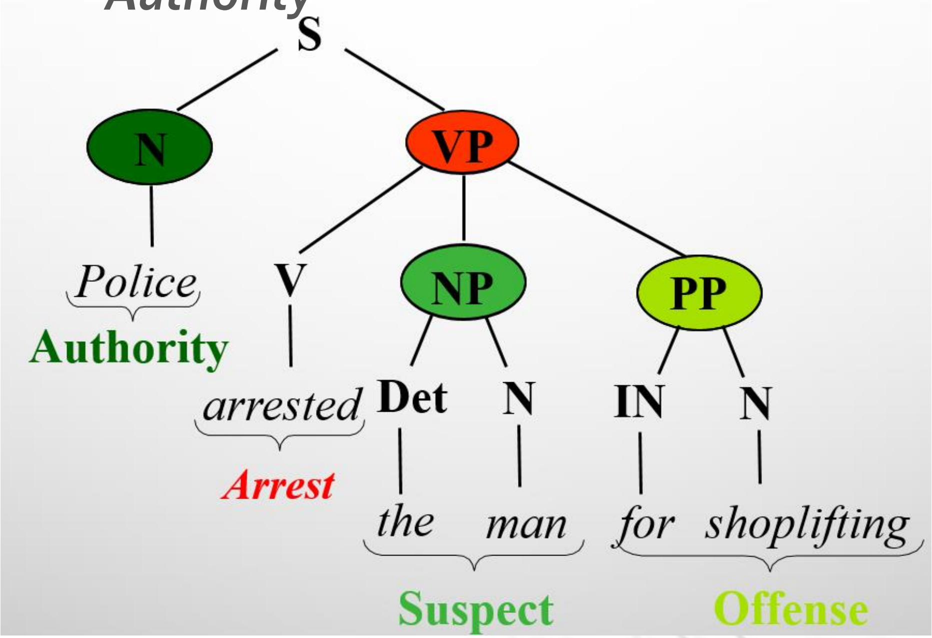
Linking syntax to semantics

- *Police arrested the man for shoplifting*



A tabular vision

- Word Predicate Semantic Role
- Police - Authority
- arrested Target Arrest
- the - SUSPECT
- man - SUSPECT
- for - OFFENSE
- Shoplifting - OFFENSE



Semantics in NLP: Resources

- Lexicalized Models
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  - NomBank
- Framenet
  - Inspired by frame semantics
  - Frames are lexicalized prototoypes for real -world situations
  - Participants are called frame elements (roles)

Frame Semantics

- Research in Empirical Semantics suggests that words represents categories of experience (*situations*)
- A *frame* is a cognitive structuring device (i.e. a kind of prototype) indexed by *words* and used to support understanding (Fillmore, 1975)
  - *Lexical Units* evoke a Frame in a sentence
- Frames are made of *elements* that express participants to the situation (*Frame Elements*)
- During communication LUs evoke the frames

Frame Semantics

Frame: KILLING		
A KILLER or CAUSE causes the death of the VICTIM.		
Frame Elements	KILLER	**John** drowned Martha.
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The FrameNet project

- The aims
  - Create a lexical resource by describing a significant portion of English in terms of precise and rich frame semantics
- The output
  - Frame Database: a structured system of Frames and Fes
  - Lexical database: syntactic and semantic descriptions of frame-evoking words (N,V,A)
  - Annotated Corpus: wide coverage examples

Killing

D

A

F

C

C

E

Instru

Seman

Exclu

Killer

Exclu

Mean

Seman

Exclu

Victin

Seman

FEs:

Non-Core:

Beneficiary [ben]	This extra-thematic FE applies to participants that derive a benefit from the occurrence of the event specified by the target predicate.
Circumstances []	Circumstances describe the state of the world (at a particular time and place) which is specifically independent of the event itself and any of its participants.

Semantic Type: Physical_entity — It's difficult to SUICIDE with only a pocketknife.

Excludes: Cause

Killer [Kill] — The person or sentient entity that causes the death of the Victim.

Excludes: Cause

Means [] — The method or action that the Killer or Cause performs resulting in the death of the Victim.

Semantic Type: State_of_affairs — The flood EXTERMINATED the rats by cutting off access to food.

Excludes: Cause

Victim [] — The living entity that dies as a result of the killing.

Semantic Type: Sentient

Non-Core:

Beneficiary [ben] — This extra-thematic FE applies to participants that derive a benefit from the occurrence of the event specified by the target predicate.

Framenet - Data

- Methodology of constructing FrameNet
  - Define/discover/describe frames
  - Decide the participants (frame elements)
  - List lexical units that evoke the frame
  - Find example sentences in the BNC and annotate them
- Corpora
  - FrameNet I -British National Corpus only
  - FrameNet II -LDC North American Newswire corpora
- Size
  - >10,000 lexical units, >825 frames, >135,000 sentences
- http://framenet.icsi.berkeley.edu

Frame Data & Domains (from G&J,2002)

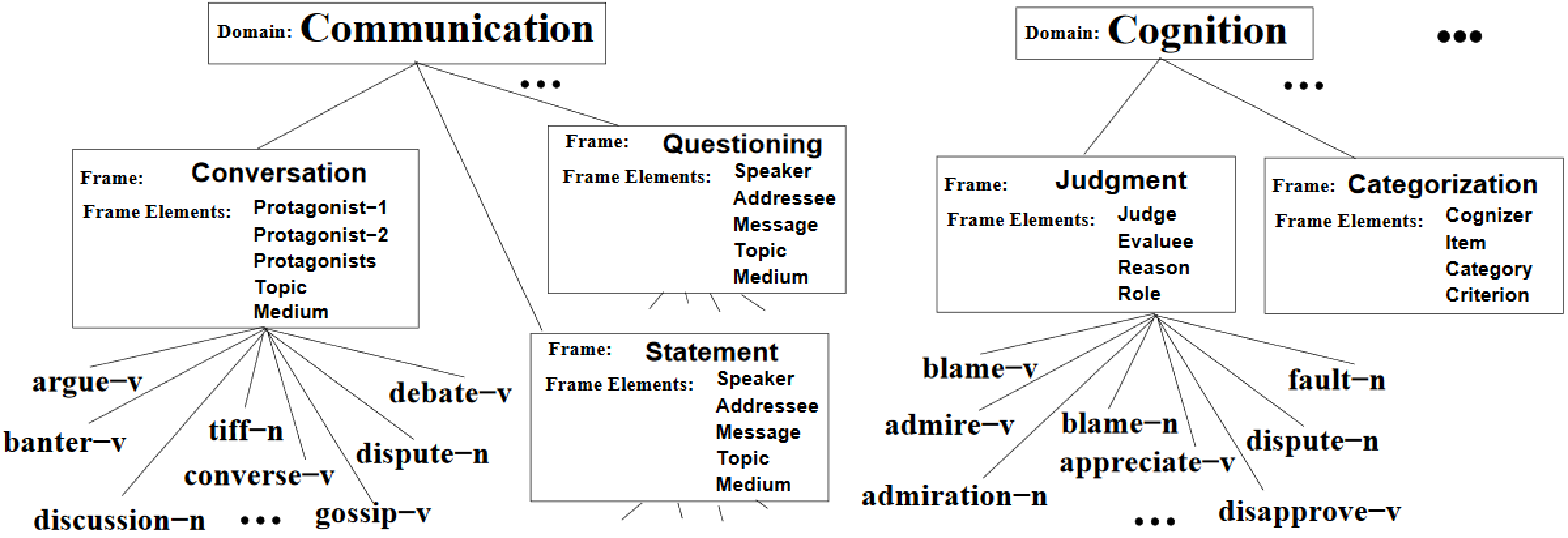
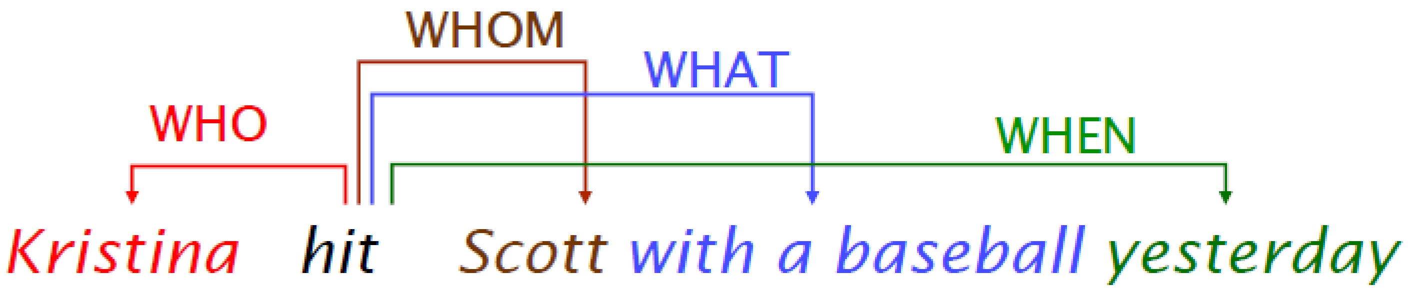


Figure 1
Sample domains and frames from the FrameNet lexicon.

Recognizing Predicates: SRL

- Semantic role labeling vs. QA



- Who hit Scott with a baseball?
- Whom did Kristina hit with a baseball?
- What did Kristina hit Scott with?
- When did Kristina hit Scott with a baseball?

Roles and variants in QA

Yesterday, Kristina hit Scott with a baseball

Scott was hit by Kristina yesterday with a baseball

Yesterday, Scott was hit with a baseball by Kristina

With a baseball, Kristina hit Scott yesterday

Yesterday Scott was hit by Kristina with a baseball

Kristina hit Scott with a baseball yesterday

- Agent, hitter
- Thing hit
- Instrument
- Temporal adjunct

SRL: task formulation

- Most general formulation: determine a labeling on (usually but not always contiguous) *substrings* (*phrases*) of the sentence *s*, given a predicate *p*

[$_{A0}$ The queen] **broke** [$_{A1}$ the window].

[$_{A1}$ By working hard], [$_{A0}$ he] **said**, [$_{C\text{-}A1}$ you can get exhausted].

- Every substring *c* can be represented by a set of word indices $c \subseteq \{1, 2, \ldots, m\}$
- More formally, a semantic role labeling is a mapping from the set of substrings of s to the label set ***L***. ***L*** includes all argument labels and NONE.

The SRL cascade

- Identification:
  - Very hard task: to separate the argument substrings from the rest in this exponentially sized set
  - Usually only 1 to 9 (avg. **2.7**) substrings have labels ARG and the rest have NONE for a predicate
- Classification:
  - Given the set of substrings that have an *ARG* label, decide the exact semantic label
- Core argument semantic role labeling: (easier)
  - Label phrases with core argument labels only. The modifier arguments are assumed to have label NONE.

ML Approaches

- **Local models** decide the label of each substring independently of the labels of other substrings

- This can lead to inconsistencies
  - overlapping argument strings

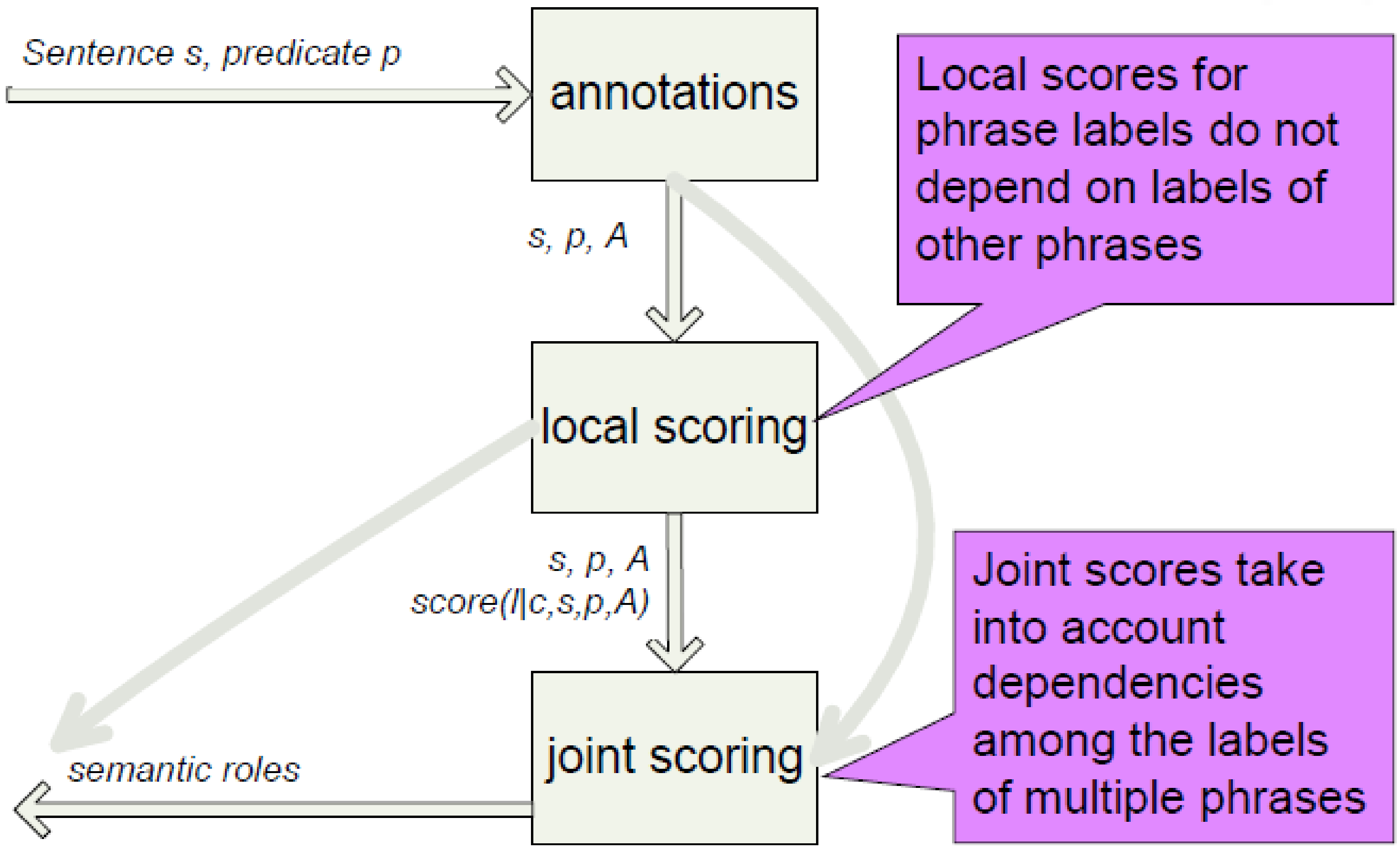
    By [$_{A1}$ working [$_{A1}$ hard] , he] ***said*** *, you can achieve a lot.*
  - repeated arguments

    By [$_{A1}$ working] hard , [$_{A1}$ he] ***said*** *, you can achieve a lot.*
  - missing arguments

    [$_{A0}$ By working hard , he] **said** , [$_{A0}$ you can achieve a lot].

- **Joint models** take into account the dependencies among labels of different substrings

The general SRL architecture



Previous work on Local …

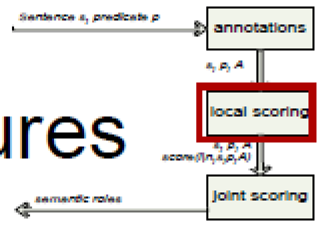
- [Gildea&Jurafsky 02]
  - **Identification + Classification** for local scoring experiments
  - **One Step** for joint scoring experiments
- [Xue&Palmer 04] and [Punyakanok et al. 04, 05]
  - **Pruning + Identification + Classification**
- [Pradhan et al. 04] and [Toutanova et al. 05]
  - **One Step**

… and Joint SRL models

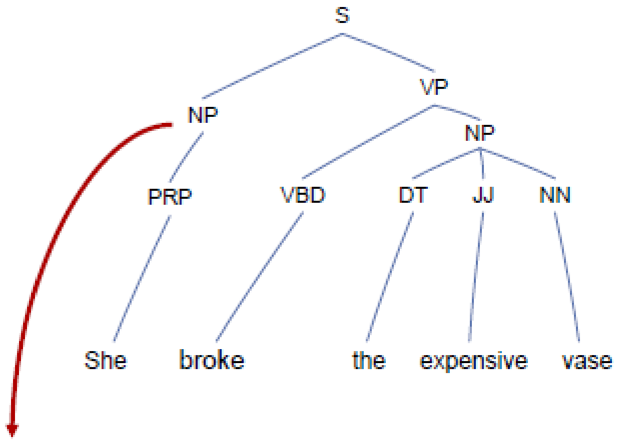
- Tight integration of local and joint scoring in a single probabilistic model and exact search [Cohn&Blunsom 05] [Màrquez et al. 05],[Thompson et al. 03]
  - When the joint model makes strong independence assumptions
- Re-ranking or approximate search to find the labeling which maximizes a combination of local and a joint score [Gildea&Jurafsky 02] [Pradhan et al. 04] [Toutanova et al. 05] [Moschitti et al. 07]
  - Usually exponential search required to find the exact maximizer
- Exact search for best assignment by local model satisfying hard joint constraints
  - Using Integer Linear Programming [Punyakanok et al 04,05] (worst case NP-hard)

Features (for Local models)

Gildea & Jurafsky (2002) Features



- Key early work
  - Future systems use these features as a baseline
- Constituent Independent
  - Target predicate (lemma)
  - Voice
  - Subcategorization
- Constituent Specific
  - Path
  - Position (*left, right*)
  - Phrase Type
  - Governing Category (*S* or *VP*)
  - Head Word



Target	*broke*
Voice	*active*
Subcategorization	*VP→VBD NP*
Path	*VBD↑VP↑S↓NP*
Position	*left*
Phrase Type	*NP*
Gov Cat	*S*
Head Word	*She*

Application of distributional lexicons for Semantic Role Labeling @ UTV

- An important application of SVM is Semantic Role labeling wrt Propbank or Framenet
- In the UTV system, a cascade of classification steps is applied:
  - Predicate detection
  - Boundary recognition (Argument Identification)
  - Argument categorization (Local models)
  - Reranking (Joint model)
- Input: a sentence and its parse trees

Tree kernels for SRL

- See «Short Introduction to Semantic Tree Kernels»

Semantic Role Labeling via SVM Learning

- Three steps:
  - Predicate Detection:
    - Locate occurrences of frames in sentences
    - Recognition of predicate words or multiword expressions
  - Boundary Detection
    - One binary classifier applied to the parse tree nodes
  - Argument Type Classification
    - Multi-classification problem, where n binary classifiers are applied, one for each argument class (i.e. frame element)
    - They are combined in a ONE-vs-ALL scheme, i.e. the argument type that is categorized by an SVM with the maximum score is selected

Automatic Predicate Argument Extraction

Deriving Positive/Negative examples

- Given a sentence, a predicate *p*:
  - Derive the sentence parse tree
  - For each node pair $<N_p,N_x>$
    - Extract a feature representation set *F*
    - If N_x exactly covers the i-th argument, *Arg-i*, *F* is one of the positive examples for an *Arg-I* classifier
    - *F* is a negative example for *Arg-I,* otherwise

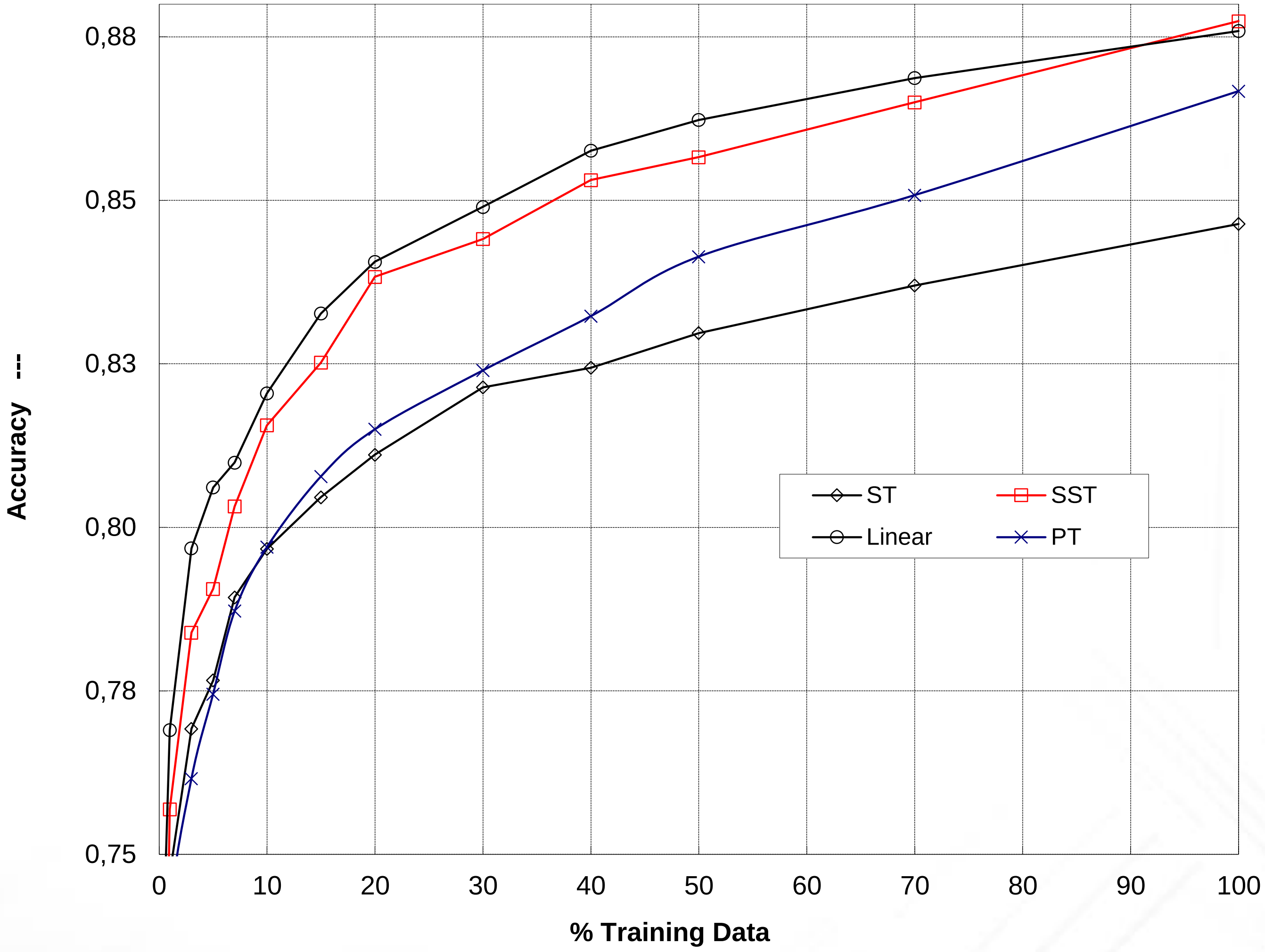
SRL at RTV: Smoothed Partial Tree Kernels

- Experimental Set-up (Croce et al., EMNLP 2011)

- FrameNet version: 1.3
- 271,560 training and 30,173 test examples respectively
- LTH dependency parser (Malt, Johansson & Nugues, 2007).
- Word space: LSA applied to the BNC corpus (about 10M words).

- Number of targeted frames: 648 frames
- Parse trees format: GRCT and LCT
- A total of 4,254 binary role classifiers (RC)

Argument Classification Accuracy



SRL in Framenet: Results

Eval Setting	Tree Kernels P	Tree Kernels R	Tree Kernels F_1	Tree Kernels + PK P	Tree Kernels + PK R	Tree Kernels + PK F_1
				PK alone		
BD	-	-	-	.887	.675	.767
BD Proj.	-	-	-	.850	.647	.735
BD+RC	-	-	-	.654	.498	.565
BD+RC Proj.	-	-	-	.625	.476	.540
	TK			**TK + PK**		
BD	.949	.652	.773	.915	.698	.792
BD Proj.	.919	.631	.748	.875	.668	.758
BD+RC	.697	.479	.568	.680	.519	.588
BD+RC Proj.	.672	.462	.548	.648	.495	.561
	TKL			**TKL + PK**		
BD	.938	.659	.774	.908	.701	.791
BD Proj.	.906	.636	.747	.868	.670	.757
BD+RC	.689	.484	.569	.675	.521	.588
BD+RC Proj.	.663	.466	.547	.644	.497	.561

Table 4.1: Results on FrameNet dataset. The table shows Precision, Recall, and F-measure achieved by the Polynomial Kernel (PK) and two different Tree Kernels (TK and TKL). Also, results for their combinations are shown. All experiments exploit 2% training data for Boundary Detection, and 90% for Role Classification.

SRL in Framenet: Results

Eval Setting	Tree Kernels P	Tree Kernels R	Tree Kernels F_1	Tree Kernels + PK P	Tree Kernels + PK R	Tree Kernels + PK F_1
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Table 4.1: Results on FrameNet dataset. The table shows Precision, Recall, and F-measure achieved by the Polynomial Kernel (PK) and two different Tree Kernels (TK and TKL). Also, results for their combinations are shown. All experiments exploit 2% training data for Boundary Detection, and 90% for Role Classification.

Framenet SRL: best results

- Best system [Erk&Pado, 2006]
  - 0.855 Precision, 0.669 Recall
  - 0.751 F1
- Trento (+RTV) system (Coppola, PhD2009)

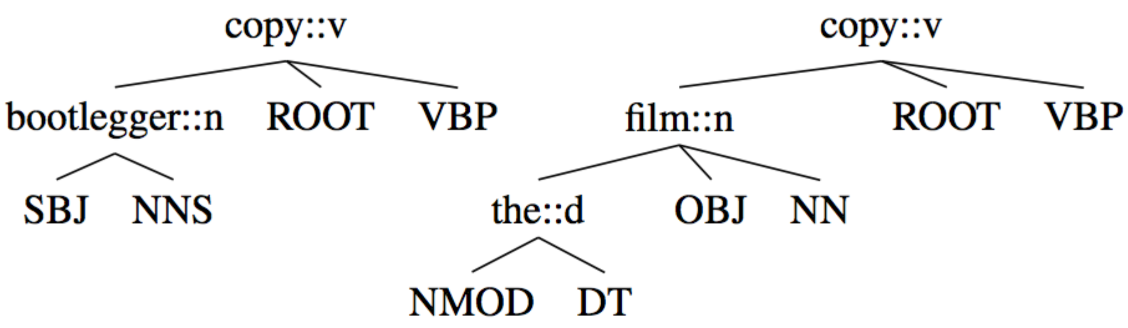
Enhanced PK+TK			
Eval Setting	P	R	F_1
BD (nodes)	1.0	.732	.847
BD (words)	.963	.702	.813
BD+RC (nodes)	.784	.571	.661
BD+RC (words)	.747	.545	.630

Table 4.2: Results on the FrameNet dataset. Best configuration from Table 4.1, raised to 90% of training data for BD and RC.

Argument Classification (Croce et al., 2013)

- UTV experimented with a FrameNet SRL classification (gold standard boundaries)
- We used the FrameNet version 1.3: 648 frames are considered
  - Training set: 271,560 arguments (90%)
  - Test set: 30,173 arguments (10%)

[*Bootleggers*]$_{CREATOR}$, *then* **copy** [*the film*]$_{ORIGINAL}$ [*onto hundreds of VHS tapes*]$_{GOAL}$



Kernel	Accuracy
GRCT	87,60%
$GRCT_{LSA}$	88,61%
LCT	87,61%
LCT_{LSA}	88,74%
GRCT+LCT	87,99%
$GRCT_{LSA}$+LCT_{LSA}	**88,91%**

Overview

- Intelligenza Artificiale e Lingue parlate e scritte
  - Informazioni e Rappresentazioni coinvolte
  - Sfide (ri)correnti, battaglie (già) vinte e rischi inerenti …
- Elaborazione Automatica delle Lingue: Modelli, Metodi e *Risultati*
- *break*
- Ruolo delle Tecnologie dell'Apprendimento ed Applicazioni:
  - Sviluppo Automatico di Dizionari, Lessici Semantici ed Ontologie
  - Riconoscimento di fenomeni semantici
  - Trattamento Semantico della Documentazione Investigativa
  - Sistemi Web-based di Opinion Mining, Market Watch & Brand Reputation Management

Distributional Semantics: the overall process

Corpus Normalization

- Remove Irrelevant Information (e.g. mark-ups)
- **Segment Texts into coherent units**

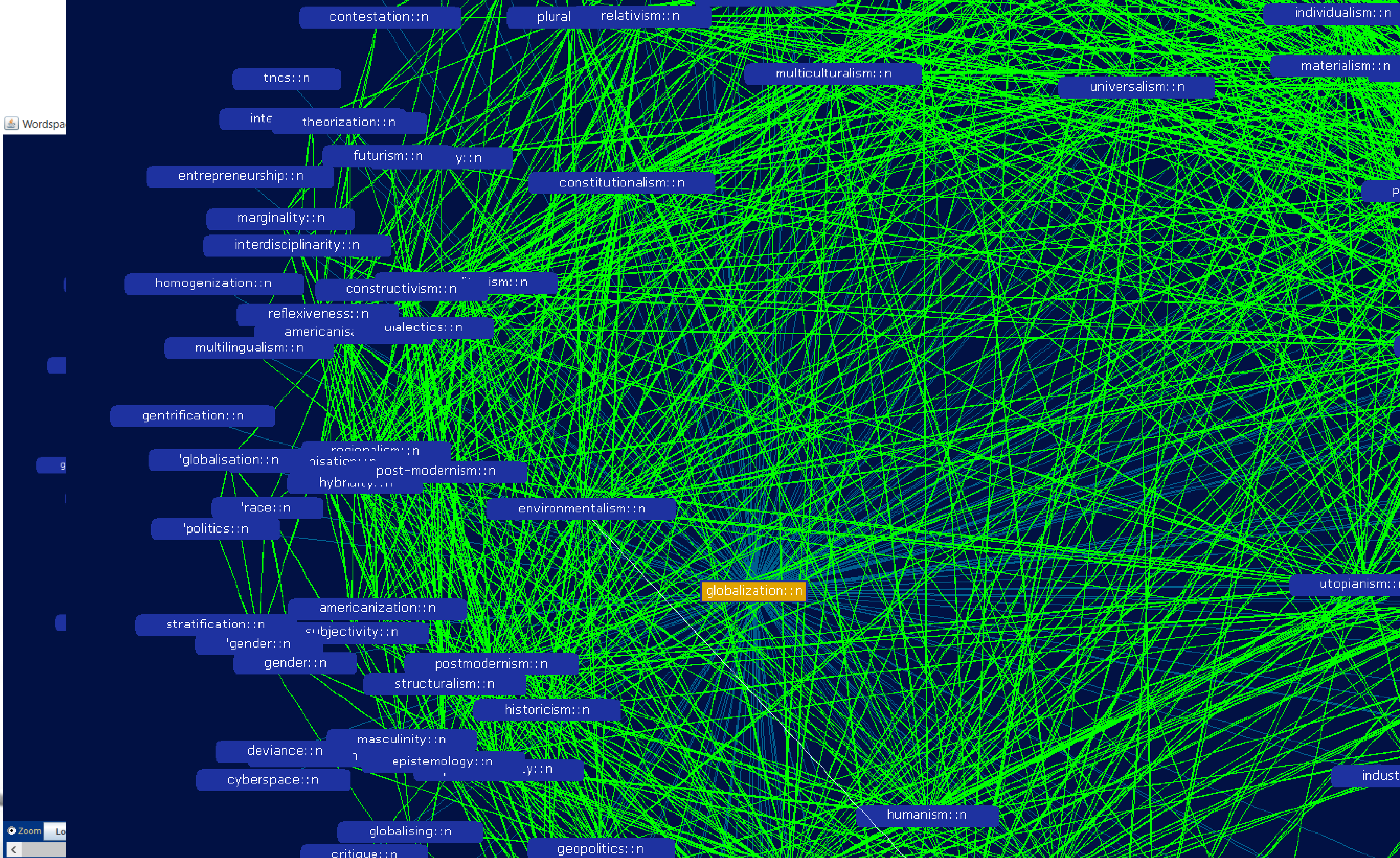
Lemmatization & Counting

- Apply **Shallow Linguistic Processing** (POS tagging)
- Build the co-occurrence **word-by-context matrix**

PCA Analysis

- Apply **SVD decomposition** of order *k*
- Map individual lexical entries into k-dimensional real-valued vectors

Latent Semantic Analysis (LSA), (Landauer & Dumais, 1997)



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plural
relativism::n
individualism::n
tncs::n
multiculturalism::n
materialism::n
universalism::n
theorization::n
futurism::n
entrepreneurship::n
constitutionalism::n
marginality::n
interdisciplinarity::n
homogenization::n
constructivism::n
reflexiveness::n
multilingualism::n
gentrification::n
'globalisation::n
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globalization::n
utopianism::n
americanization::n
stratification::n
'gender::n
gender::n
postmodernism::n
structuralism::n
historicism::n
masculinity::n
deviance::n
epistemology::n
cyberspace::n
humanism::n
globalising::n
geopolitics::n
Zoom


he is running the Marathon this year
play::v$$0.505
host::v$$0.550
build::v$$0.574
call::v$$0.523
visit::v$$0.519
attend::v$$0.521
close::v$$0.520
base::v$$0.495
hold::v$$0.621
support::v$$0.527
open::v$$0.632
She is running a relief operation in Sudan
enter::v$$0.568
deliver::v$$0.500
run::v
return::v$$0.506
reach::v$$0.563
offer::v$$0.496
move::v$$0.626
leave::v$$0.505
install::v$$0.520
turn::v$$0.608
set::v$$0.605
take::v$$0.585
go::v$$0.581
connect::v$$0.510
start::v$$0.645
put::v$$0.530
Running a new program on a PC
get::v$$0.495
The children ran to the store

Automatic Acquisition of distributional semantic lexicons from corpora

- Three main approaches
  - Bayesian models, e.g. Topic models or LDA
  - Algebraic models, ususally based on matrix decomposition (e.g. LSA)
  - Neural models, e.g. self-associative (auto)encoders (Mitkov, 2013)

- All methods output n-dimensional lexical vectors that corresponds to units of semantic descriptions
- The overall vector set is called *word embedding* and it corresponds to an implicit representation of the mental lexicon

Semantics, Natural Language & Learning

- From **Learning to Read** to **Knowledge Distillation** as a (integrated pool of) Semantic interpretation Task(s)
  - **Information Extraction**
    - Entity Recognition and Classification
    - Relation Extraction
    - Semantic Role Labeling (Shallow Semantic Parsing)
  - **Estimation of Text Similarity**
    - Structured Text Similarity/Textual Entailment Recognition
    - Sense disambiguation
  - **Semantic Search, Question Classification and Answer Ranking**
  - **Knowledge Acquisition**, e.g. ontology learning
  - **Social Network Analysis, Opinion Mining**

Overview

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  - Informazioni e Rappresentazioni coinvolte
  - Sfide (ri)correnti, battaglie (già) vinte e rischi inerenti …
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  - Trattamento Semantico della Documentazione Investigativa
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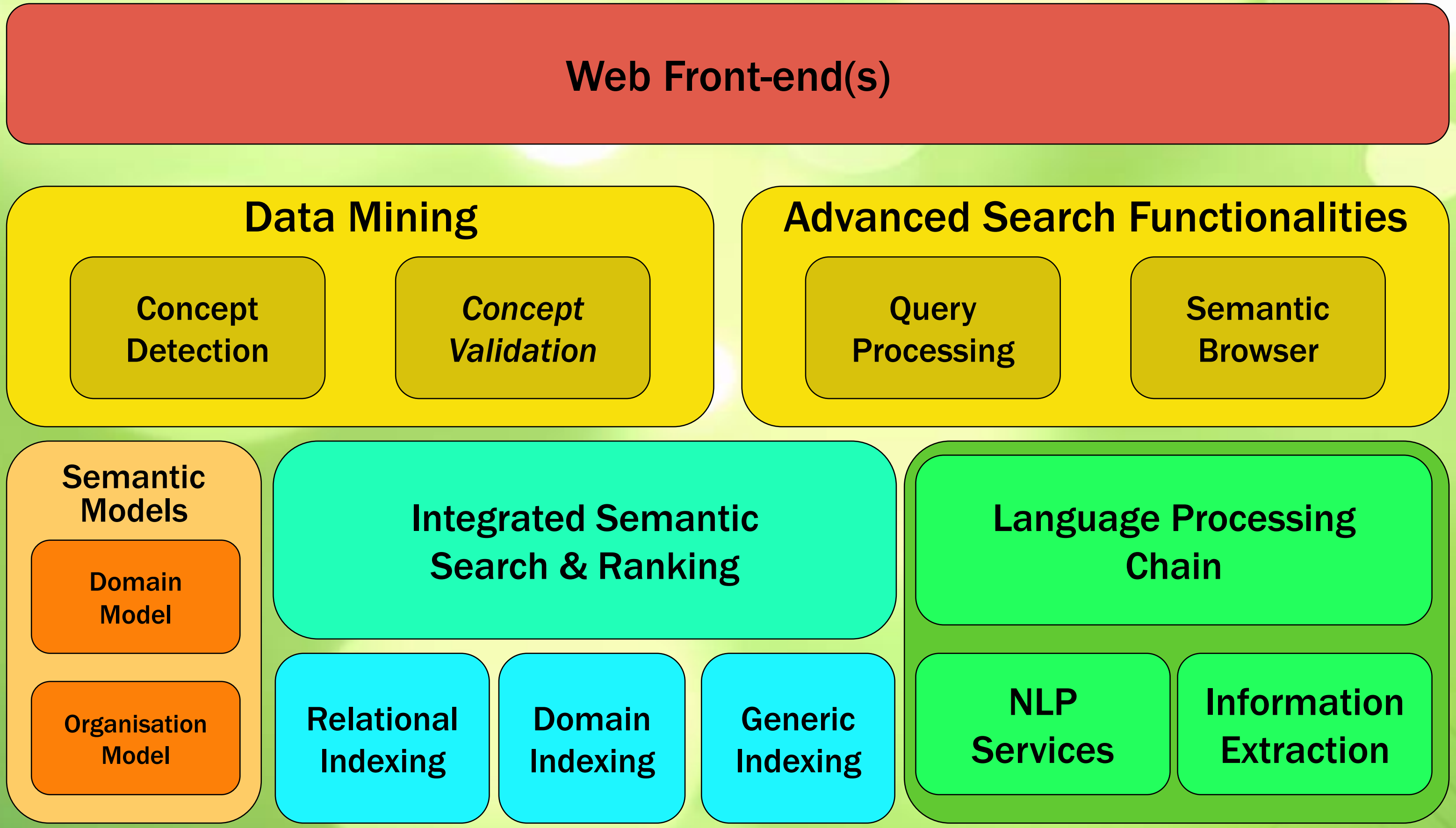
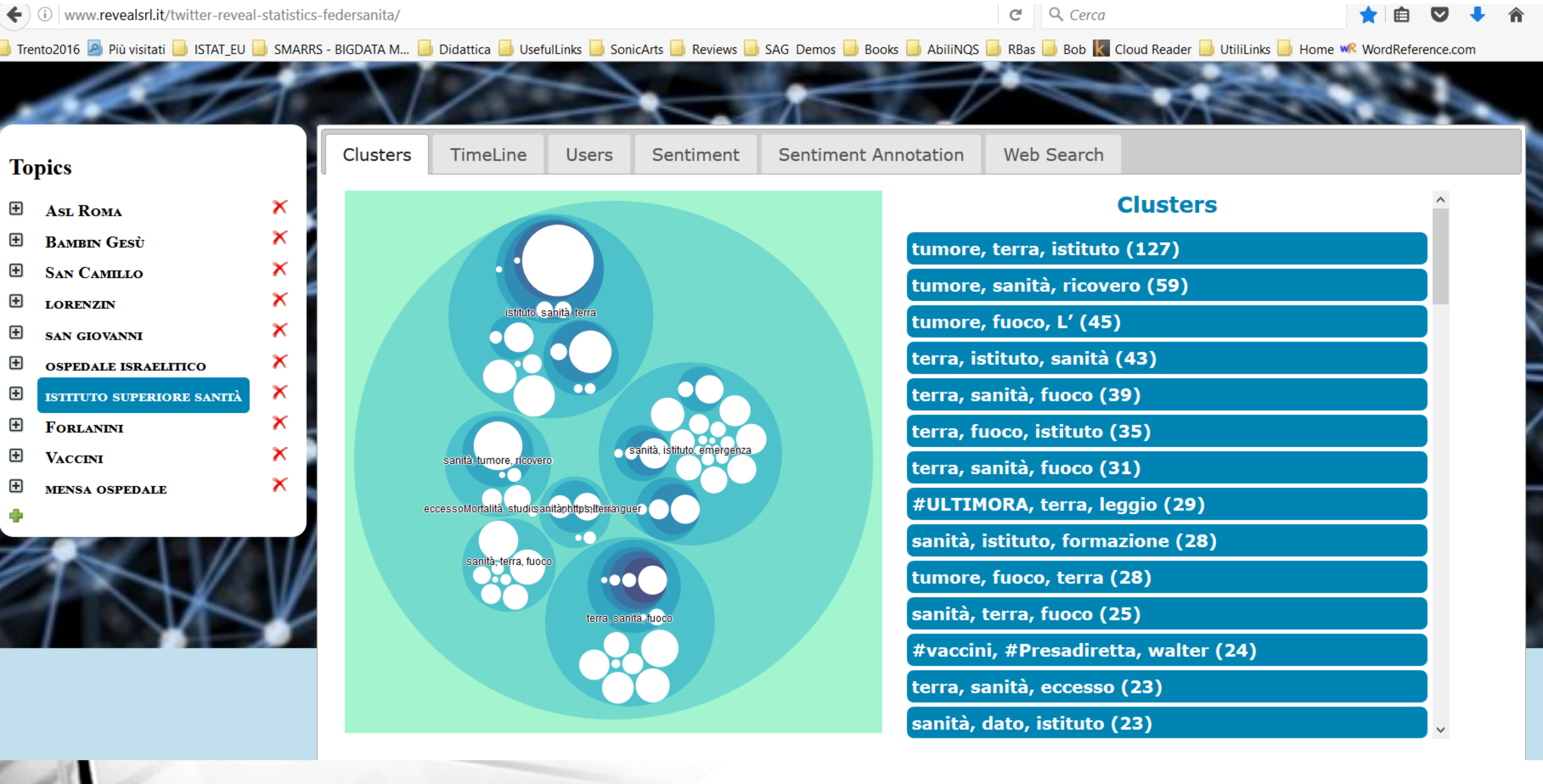
The typical Semantic Search Architecture

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terra, fuoco, istituto (35)
terra, sanità, fuoco (31)
#ULTIMORA, terra, leggio (29)
sanità, istituto, formazione (28)
tumore, fuoco, terra (28)
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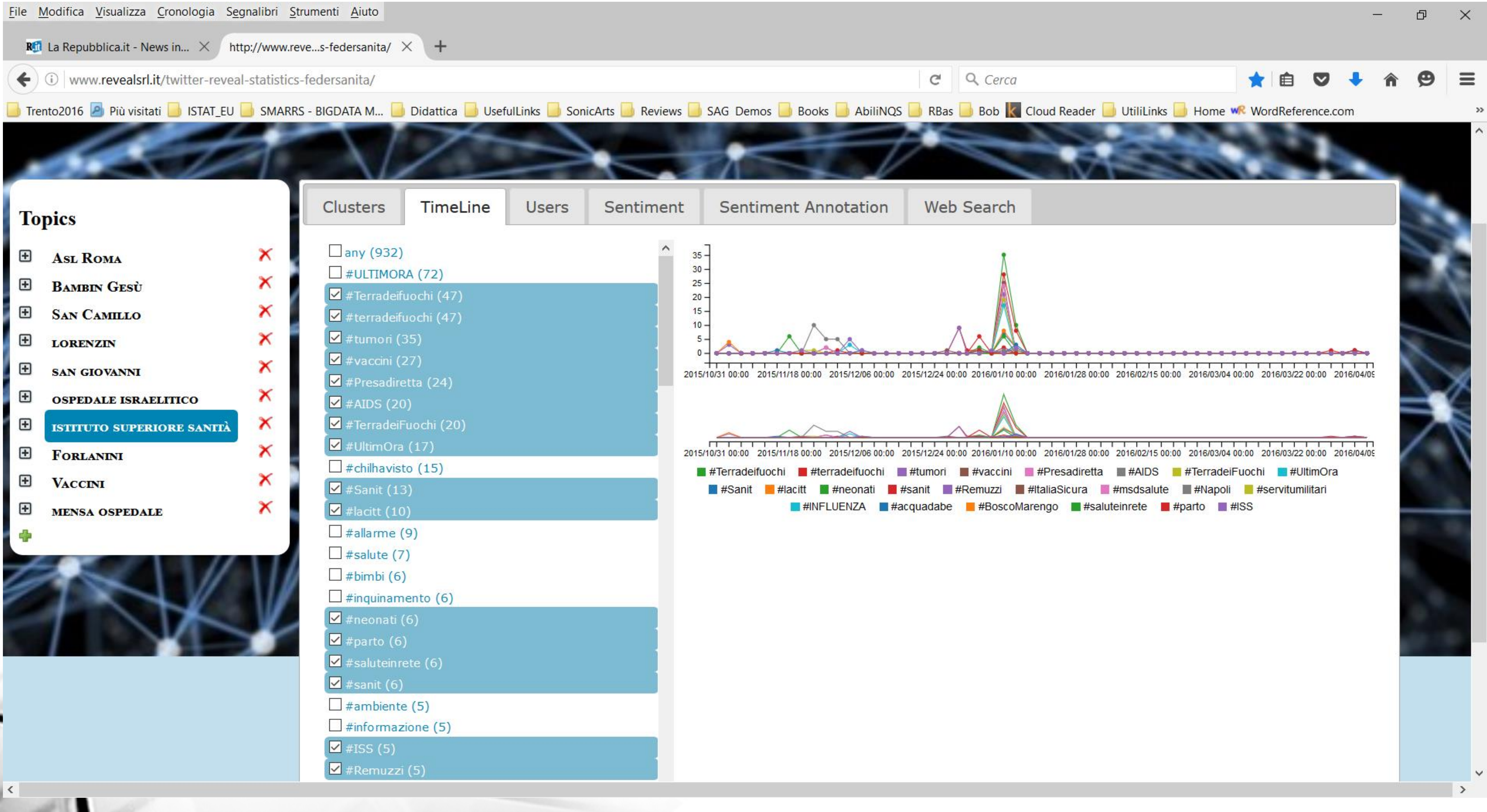
#vaccini, #Presadiretta, walter (24)
terra, sanità, eccesso (23)
sanità, dato, istituto (23)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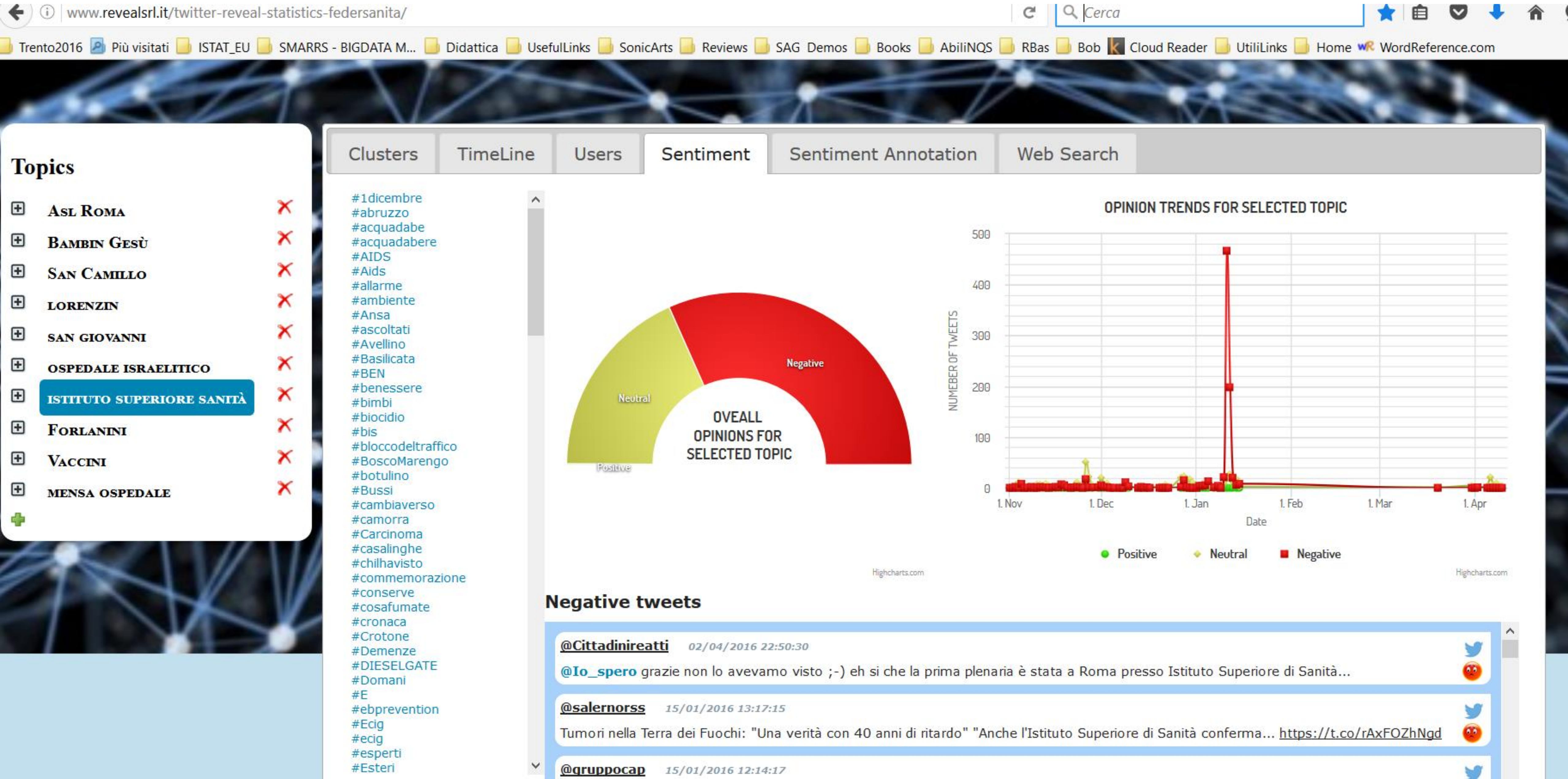
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1. Jan
1. Feb
1. Mar
1. Apr
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Neutral
Negative
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Highcharts.com
Negative tweets
@Cittadinireatti 02/04/2016 22:50:30
@Io_spero grazie non lo avevamo visto ;-) eh si che la prima plenaria è stata a Roma presso Istituto Superiore di Sanità...
@salernorss 15/01/2016 13:17:15
Tumori nella Terra dei Fuochi: "Una verità con 40 anni di ritardo" "Anche l'Istituto Superiore di Sanità conferma... https://t.co/rAxFOZhNgd
@gruppocap 15/01/2016 12:14:17

Conclusioni

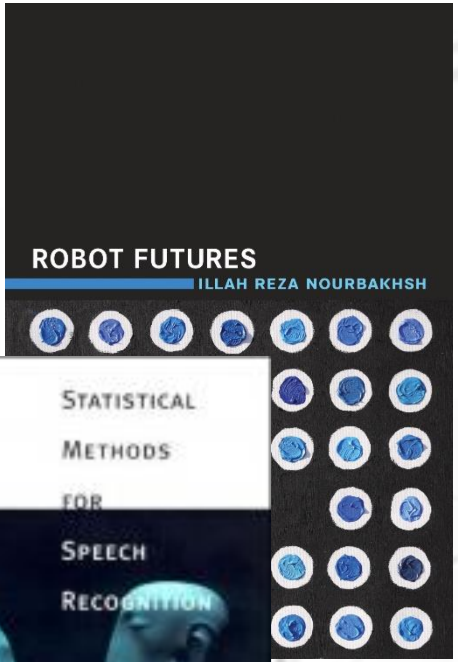
- I dati della odierna società della conoscenza sono opachi dal punto di vista epistemologico e l'intermediazione dei sistemi di calcolo deve sostenere processi complessi di interpretazione
- Le tecnologie del linguaggio e l'impulso loro dato dai metodi di Machine Learning possono svolgere un ruolo fondamentale nel sostenere in modo accurato i processi agenti sui Big Data e nel renderli economicamente sostenibili
- La tipica catena di elaborazione NLP è costituita da 4 fasi principali: Lexical Analysis, Syntactic Analysis, Semantic Analysis e Pragmatic (cioè Application-dependent) Analysis.
  - Le tecnologie di supporto alle tre fasi si basano su risorse (dizionari, lessici, grammatiche e basi di conoscenza) molto estese e dipendenti spesso dal dominio e dalla applicazione
  - Le tecnologie di Machine Learning consentono di abbattere i costi di messa a punto delle diverse componenti nei diversi domini di applicazione
  - Abbiamo approfondito alcuni compiti semantici (cioè legati alla fase di Analisi Semantica) come use cases nella aplicazione ML al NLP
    - Semantic Role Labeling
    - Named Entity Recognition and Classification

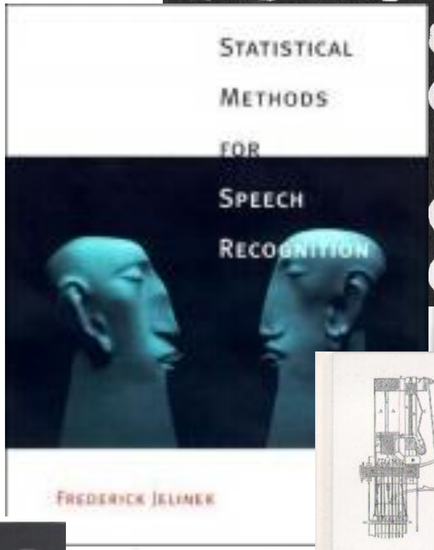
Conclusioni (2)

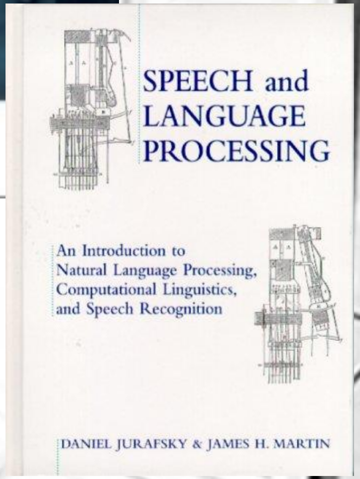
- I processi di AI (NLP&ML) costituiscono una branca attiva dell'Informatica che determina in modo rilevante il successo di processi innovativi della automazione in ambito industriale
  - Gestione Documentale
    - Metadatazione semantica
    - Indicizzazione
  - Semantic Search
    - Possibilità di gestire interrogazioni complesse (in NL) verso basi documentali estese indicizzate semanticamente in precedenza
  - Opinion Analysis & Brand Reputation
    - Analisi delle fonti aperte
    - Classificazione tematica ed emotiva
    - Business Intelligence sui livello dei contenuti e della emotività

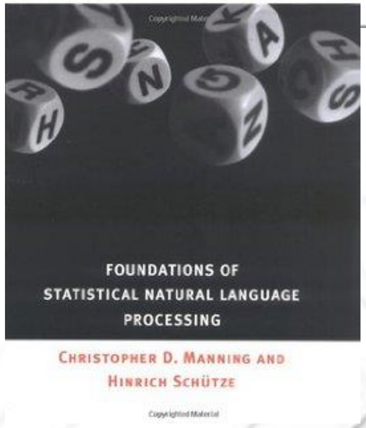
Riferimenti

- AI & Robotics. «Robot Futures», Ilah Reza Nourbakhsh, MIT Press, 2013
- NLP & ML:
  - «Statistical Methods for Speech Recognition», F. Jelinek, MIT Press, 1998
  - «Speech and Language Processing”, D. Jurafsky and J. H .Martin, Prentice-Hall, 2009.
  - “Foundations of Statistical Natural Language Processing, Manning & Schtze, MIT Press 2001.
- Sitografia:
  - SAG, Univ. Roma Tor Vergata: http://sag.art.uniroma2.it/
  - Reveal s.r.l.: http://www.revealsrl.it/









Riferimenti Bibliografici per il Corso

- Wordnet, Framenet:
  - Jurafsky-Martin «SPEECH and LANGUAGE PROCESSING» (http://www.cs.colorado.edu/~martin/slp.html), Chapt. 17, 19
- Semantic Role Labeling:
  - Jurafsky-Martin Book, Chapt. 10
  - Gildea, D. & Jurafsky, D. (2002). Automatic labeling of semantic roles. Computational Linguistics, 28:3, 245–288
  - S. Pradhan, et al., "Support Vector Learning for SRL", Journ. of Machine Learning, 60, 11–39, 2005, (URL: https://www.cs.colorado.edu/~martin/Papers/srl-ml-journal05.pdf).
  - Croce, D., Moschitti, A., & Basili, R. (2011). Structured lexical similarity via convolution Kernels on dependency trees. In EMNLP 2011: Conf. on Empirical Methods in NLP, 1034-1046, 2011.
- Named Entity Recognition
  - D.M. Bikel, R.L. Schwartz, R.M. Weischedel. 1999. An algorithm that learns what's in a name. Journ. of Machine Learning , 34(1-3):211–231